TREE CANOPY COVERAGE FOR THE CITY OF ATLANTA:

A Methodology Definition, Geography Assessment, and City Comparison

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ABSTRACT

The City of Atlanta does not have a current inventory for its urban tree canopy coverage, let alone urban vegetation as a whole, within the city limits. It is important, though, to have an inventory of vegetated land cover classes in terms of planning implications. Urban vegetation and tree canopy coverage have beneficial externalities for cities. After studying a literature review of ten articles, four themes of the positive externalities of urban vegetation and tree canopy coverage arose: environmental, hydrologic, urban design, and socioeconomical. The environmental category includes reducing urban heat island effects, energy savings, lowering cities' temperatures, protecting wildlife habitats, and managing air quality. The hydrology category involves stormwater management, managing water quality, flood possibility reduction, and erosion prevention. The urban design category points to improvements in urban aesthetics, walkability, contributing to sense of place, increasing privacy while decreasing noise pollution, and crime reduction. The socioeconomic category includes raising property values, increasing community pride and health, and positively contributing to quality of life.

After the justification of the benefits of urban vegetation and tree canopy coverage, a methodology of obtaining these land covers is outlined. First, the study area of the City of Atlanta is described. A review of other studies' methodologies contributes reasoning for the following process outlined for Atlanta. Using Quickbird satellite imagery from October, 2008, two methodology processes are outlined: human-defined and computer-defined. The human-defined process has two major steps, which are to subset a general vegetation class, called an NDVI equation, before performing a supervised classification, meaning the user has great knowledge of the ground environment. The computer-defined process, unsupervised classification, is only one major step and allows the machine to determine an input amount of classes; in this case, the computer defined 100 different classes.

Once the two classification processes are complete, an accuracy assessment is performed for both. The process with the highest accuracy is the human-defined process, or the supervised classification of the NDVI subset image. This process received an overall accuracy of 78.67 percent compared to the unsupervised classification's 66.00 percent overall accuracy. Using the human-defined outcome, the City of Atlanta has 58,694 acres of urban vegetation (68.65 percent of the city's total land area) and 44,841 acres of tree canopy coverage (52.45 percent of the city's total land area). Seemingly, the main issue with the computer-defined process is the presence of a shadow class that the supervised classification process did not include; rather, the user interpolated the land cover that the shadow is covering.

In establishing a methodology to obtain an inventory of urban vegetation and tree canopy cover, planners, decision-makers, and stakeholders can interpolate vegetation coverage percentages for various geographies of the City of Atlanta, including land use categories, watersheds, police beats, census blocks, city council districts, and neighborhood planning units. Further action in the growth, management, and maintenance of Atlanta's vegetation land cover classes includes land suitability analyses, repeating analysis to interpolate changes in land cover classes, a more in depth demographic study, and regionally internal and external comparisons.

THE BENEFITS OF URBAN VEGETATION AND TREE CANOPY COVERAGE

Missing Urban Tree Canopy Inventory

The City of Atlanta has had many quotes made about its urban vegetation and tree canopy cover. However, no legitimate study has been done to reach such conclusions. The purpose of this study is to determine the total amount of vegetation and ultimately the total amount of urban tree canopy coverage within the city's political limits. The areas of each of these land covers are determined by remote sensing techniques performed on satellite imagery; the specific remote sensing techniques are discussed further and in much more detail throughout the methodology section below. The process intends to differentiate between vegetated land cover and non-vegetated land cover. More specifically, the urban tree canopy cover is extracted from the vegetation leaving both the urban vegetation and tree canopy coverage as accounted for land cover classes.

Both urban vegetation and urban tree canopy coverage inventories are important in contributing to the health, welfare, and equity within a city. After examining ten studies that span over the past thirty years, some important themes that legitimize the act of identifying urban vegetation and tree canopy coverage inventories arise. These studies and their results are detailed below.

Urban Vegetation Literature Review

Urban vegetation and tree canopy coverage is incredibly important. The City of Atlanta has never conducted a study to determine an inventory of its tree canopy coverage let alone vegetation in general. Urban vegetation records are important in determining specifics like stormwater runoff coefficients, which is an environmental systems measure. However, urban tree canopy coverage on its own, rather than a part of urban vegetation land coverage, is generally the most reported by municipalities. The area of urban tree canopies have many more implications in respect to many aspects of city life, including environmental, hydrology, urban design, and socioeconomic. These four categories are listed in table 1 below along with the factors that make up each category. For the environmental factors that urban vegetation and tree canopy coverage have an effect on are urban heat island effect, energy savings, temperature lowering, wildlife habitat, and air quality. The hydrological factors are stormwater management, water quality, flood reduction, and erosion prevention. The urban design factors are aesthetic improvements, walkability, sense of place, privacy/noise, and crime reduction. Lastly, the socioeconomic factors that urban vegetation and tree canopy coverage have an effect on are raising property values, community pride/health, and quality of life. The categories' sub factors are also listed in table 1. The table ultimately outlines, chronologically, ten studies on what each reviewer feels to be the important factors that have a positive relationship with urban vegetation and tree canopy cover. Nine of the studies range over nearly thirty years and across the United States, while the tenth is the contract that Georgia Tech's CGIS and CQGRD has with the City of Atlanta to develop the methodology for the city's urban vegetation and tree canopy cover inventory. Each has its own particular focus, but trends and similarities appear throughout the ten studies. Further detail of each study is detailed below.

TABLE 1: LITERATURE REVIEW RESULTS

	FACTOR	Sanders 1986	McPherson & Rowntree 1993	Nowak et al. 1996	Dwyer & Miller 1999	Nowak et al. 2001	Heynen & Lindsey 2003	Heynen et al. 2006	Nowak 2006	CGIS, GCQGRD 2012	Ramsey County GIS User Group 2012
ENVIRON MENTAL	Urban Heat Island Effect		*			*		*		*	
	Energy Savings		*	*	*	*	*	*	*	*	
	Temperature Lowering		*		*		*			*	*
	Wildlife Habitat			*	*		*	*		*	
	Air Quality		*	*	*	*	*	*	*	*	*
HYDRO LOGY	Stormwater Management	*			*	*	*	*			*
	Water Quality	*			*			*	*	*	*
	Flood Reduction	*			*	*	*	*		*	
	Erosion Prevention	*			*					*	
URBAN DESIGN	Aesthetic Improvements					*	*			*	
	Walkability									*	
	Sense of Place					*	*			*	
	Privacy/Noise					*	*	*		*	
	Crime Reduction									*	
SOCIO ECON OMIC	Raising Property Values					*	*				*
	Community Pride/Health		*	*		*	*				*
	Quality of Life		*			*	*	*	*		

Sanders (1986) goes into specifics about the effects of urban vegetation and tree canopy coverage on stormwater management. Developed urban land accounts for much more rainwater runoff than the pervious surfaces as compared to urban vegetation. The increased runoff amounts caused by developed urban land also increases the amount of sewage infrastructure necessary and the amount of filtering technologies necessary for re-emitting the water back into usage. Conversely, tree canopy and vegetation coverage not only allow for water seepage into the ground rather than into a sewage system, it also allows for a natural filtering system. The addition of more developed urban land while lessening urban vegetation greatly impacts rainwater runoff system characteristics. In general, the author found that "urban tree canopies reduce runoff by an order of magnitude of about ten percent during periods of heavy precipitation, [suggesting] that the hydrologic benefits provided by trees and grasses in the city, when coupled with other benefits vegetation produces, justify city management efforts to support programs to 'plant for climate'" (Sanders, 1986, p. 362-363).

In reference to water runoff, it is a very complex system that determines the amount and quality of output, but it is simple in realizing that the less amount of impervious surface, the easier it is for stormwater management systems. The author argues that not only is it cheaper to not develop vacant land, the city also saves money in the handling of stormwater; it is a cyclical relationship. To illustrate the intense differences between varying levels of urban vegetation, while holding all other variables constant, Sanders analyses runoff using existing land cover characteristics, a modest achievable increase in vegetation, and land cover that removes all urban vegetation. Also taken into account are land use types, which allow for different amounts of water runoff; land use planning can help to encourage development that is stormwater-runoff-friendly. Four land cover and soil types were derived as important for analysis, including artificially surfaces areas (impervious or developed land), exposed soil, herbaceous cover, and tree canopy coverage. Although, a data limitation occurs in that the understories of the tree canopy coverage remained uninterpreted. Via looking at land use and land cover together in each of the three scenarios of varying levels of urban vegetation, the author determined that open, non-artificially-covered urban spaces drastically reduces the cost of stormwater management, and soil type is very important in determining runoff, meaning that individual watershed studies are appropriate and necessary in obtaining accurate rainwater runoff results.

McPherson & Rowntree (1993) address whether or not the addition of trees in urban areas is a cost-effective way to reduce the environmental woes causes by the current inefficient energy consumption practices of cities. It is important that professions across the board think about alternative possibilities to ameliorate the negative externalities of city life. Specifically, the authors delve into the effects of vegetation on urban climate. Shading of trees reduces the "amount of radiant energy absorbed, stored, and radiated by built surfaces" is merely one of the many ways in which trees help to control the climate in a positive way (McPherson & Rowntree, 1993, p. 321). The authors also speak to the potential of expanding the urban tree land cover, which is based on the varying types of land use; saturation levels are generally higher for parks and residential land uses rather than commercial and urban cores. Likewise, the older the neighborhood, the more likely the land cover is to be consisted of tree canopy. Knowing these generalities of tree canopy land coverage, appropriate policy action can be taken to enhance the numbers of trees in cities.

Nowak et al. (1996) relay that aerial imagery and remote sensing are often the most cost effective way to obtain a detailed inventory of land cover, tree canopy included. Using historical aerial imagery in comparison with current images illustrates land cover changes that can help planners determine canopy morphology patterns, good and bad. The authors detail multiple methods for figuring urban tree canopy coverage, two of which include crown cover scale, which compares a sampling of individual trees' aerial crown size to its ground characteristics in order to interpolate an applicable standard for a city's entire tree population, and the scanning method, which is heavily based on the integrated GIS system's raster analysis from ortho-rectified imagery. Although labor intensive, GIS methods can help to identify forest fragmentation and possible corridor locations for future connectivity, which is shown to promote the health and growth of biodiversity.

The authors refer to potential natural vegetation as vegetation that "would exist today if humans were removed and plant succession were allowed to continue to climax condition," with resulting natural vegetation land cover classes as forest, grassland, and desert/shrubland (Nowak et al., 1996, p. 51). These classes were derived based on the idea that the different coverages can have different saturations per land use types. The study takes into account, too, that cities in less lush geographic regions can be limited to a smaller maximum amount of urban tree canopy coverage than cities in more forested areas. Overall, the two factors that affect urban tree canopy coverage the most are the surrounding natural environment and land use. Cities with higher amounts of annual precipitation and higher amounts of available space for vegetation, such as residential lots and parks, will also have higher amounts of tree canopy cover.

Dwyer & Miller (1999) discuss the importance of determining an appropriate inventory of urban forests because it is imperative in tree maintenance, replacement, and continued planting. Specifically, they dissect the greater Stevens Point area's urban tree coverage, located in Wisconsin. In general, planners need to know land uses to "direct future patterns of growth and greenspace development," which includes a city's tree canopy coverage (Dwyer & Miller, 1999, p. 102). Furthermore, the authors lay out benefits from urban tree coverage: cooling air temperatures especially in the summer seasons, which will reduce the demand for air conditioning and relatedly reduce communities' demand for fossil fuels; reducing flooding that is caused by the increased presence of the impermeable surfaces of urban environments; replenishing the groundwater supply by decreasing built land covers; and many other benefits including bettering urban air quality.

According to Nowak et al. (2001), city size is increasing exponentially, which means a detailed inventory of urban forests is needed in order to maintain a healthy urban ecological environment. Due to the great increase of population and city size, planners need to mitigate human impact on the earth. The increase of urban populations is accompanied by an increase of poorer populations whom have fewer opportunities to travel. Hence, "[t]he urban forest may be the only forest that some urban residents will ever experience, [meaning] urban forests can provide a context for the values that urbanites place on forests in general" (Nowak et al., 2001, p. 38). Furthermore, urban forests can be laboratories for all city dwellers to directly manage natural resources; a hands-on approach to urban forestry will help to induce a sense of ownership and pride in one's community.

This study looked at remotely sensed geographic data and compared it against Census derived demographic data to generate to estimate a relationship between the two data inputs, including tree coverage area per person in cities across the United States. Variation occurred, which the authors attributed to three factors: ecoregion type, population density, and land use. Urban forests are more prevalent in cities that were originally developed within forested ecoregions, their density drops as population density rises, and their patterns tend to follow land use trends with more trees in vacant, undeveloped lands. Overall, this study intends to show the importance of the interdependent relationship between urban growth, urban influence, and natural resource systems; in general, a change in any environment, whether it be the influx of urbanity, can have effects on an ecosystem.

Heynen & Lindsey (2003) state that, due to advanced GIS and remote sensing methods, inventories of urban forests are becoming easily attainable. Thus, an improvement on said forests management, maintenance, and expansion should be inevitable. Also derived from these advanced methods is the fact that on a national scale, urban forests are greatly lacking. Cities' public works departments need to utilize the data that GIS and remote sensing outputs in order to respond better to urban forest deficits. After naming numerous benefits of urban forestry, the authors state that "[e]conomists have shown that [said] benefits may outweigh the costs of urban forestry programs by considerable margins" (Heynen & Lindsey, 2003, p. 34). Furthermore, the organization American Forests recommends an average of 40 percent tree land coverage for urban areas, in which a mix of land uses is necessary because some land use types inherently do not have as much tree canopy coverage as others.

The authors go on to discuss why such variation exists today in urban vegetation of municipalities across the nation. In the study four main categories of importance surfaced while researching current available data considering canopy cover variation, which are ecological and geographic factors, urban morphology or form, socioeconomic factors, and local policy. Ecologically and geographically, it is generally less attractive to develop areas with steeper slopes or in flood plains. Areas with more of these types of geographic areas are more likely to have open space that can be reserved for tree canopy coverage. In reference to urban morphology and form, residential density generally has a negative relationship with urban vegetation because concentrated populations strain nature. Likewise, the more historical parkland the more likely is the existence of tree canopy coverage. Socioeconomically, trees are shown to add economic value to property, thus urban canopy coverage can be said to be related positively with socioeconomic factors, like household income, education, and race. Lastly, public policy, such as comprehensive plans, often regulate where open space and tree planting can occur. The policy category is linked back to socioeconomic factors in that plans are more likely to focus on social services than urban vegetation measures in areas that have poorer residents.

In a case study in Milwaukee, Wisconsin, Heynen, Perkins, & Roy (2006) focus on social inequity in urban environments and argue that social hierarchies produce uneven physical environments. In other words, the city environment changes, or transforms, from block to block based on the residents' socioeconomic status. Included in this transformation is the lack of a presence of urban vegetation in the areas populated with residents of lower socioeconomic statuses; conversely, this hypothesis is only applicable in urban areas and not in their rural, poorer counterparts. While listing numerous benefits of urban forests, they focus on the idea of environmental justice spread evenly across cities to mitigate the negative externalities related to a lack of urban vegetation.

The authors see current urban vegetation environments as a result of physical frameworks and consumption, and "these relational processes of commodification produce urban forests that epitomize past and present structural processes inherent in urban political economy, such as income inequality, uneven property ownership, and the increase marketization of nature" (Heynen, Perkins, & Roy, 2006, p. 4). Urban residents, consciously or not, recognize the inherent benefits of urban forests, making nature desirable. Urban forest are becoming less and less naturally occurring while becoming more and more of a commodity. To illustrate the problem, the authors map urban canopy cover and various demographic statistics per U.S. Census block group, which shows a positive relationship between urban vegetation and socioeconomic status. They suggest regreening cities to lessen environmental injustice issues.

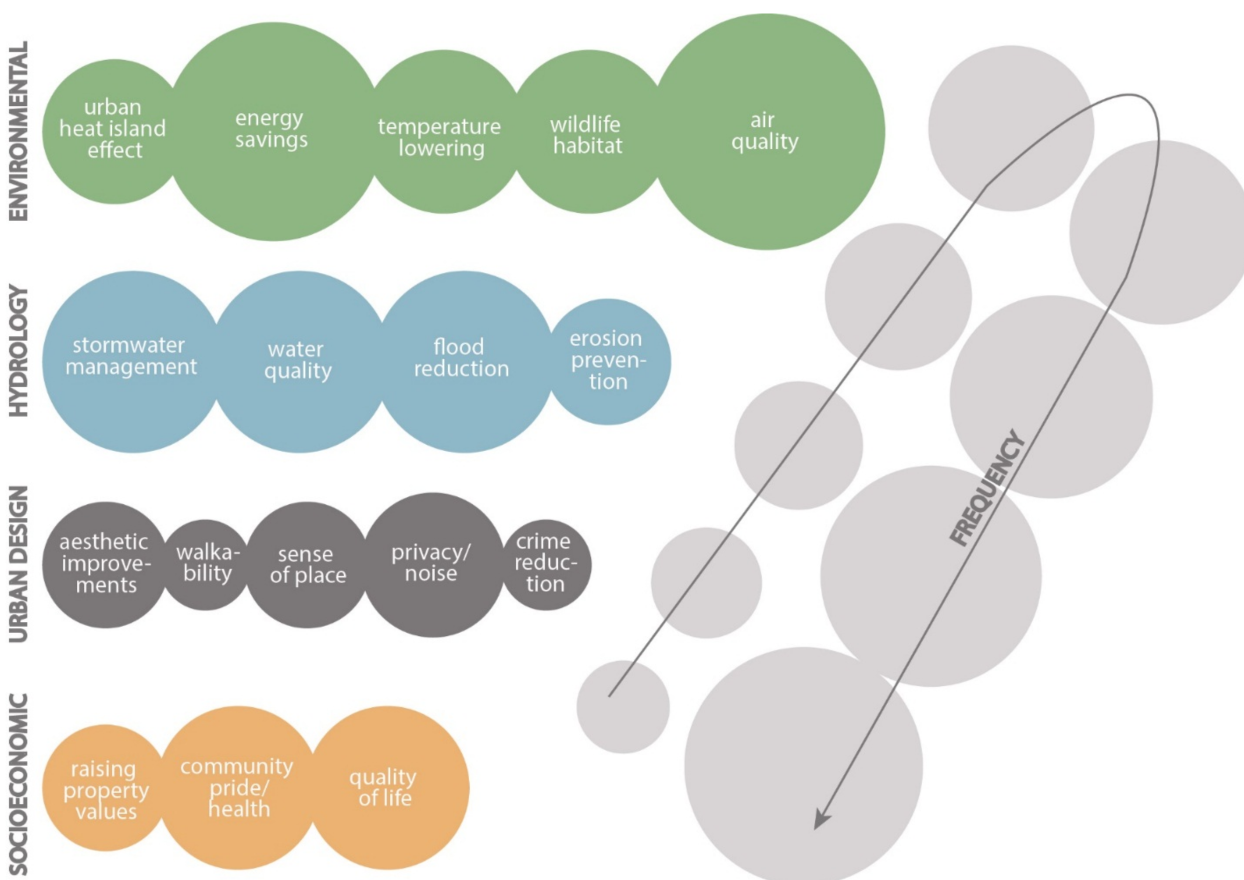
Nowak (2006) discusses the need to incorporate urban vegetation management into planning, policies, and regulations to improve environmental and social qualities of urban areas. This study hopes to "detail the effects of urban forests on air quality and streams flows in particular cities and discuss the role of urban forests within national programs/regulations related to environmental quality and human health" (Nowak, 2006, p. 94). Using on-the-ground data to infer tree characteristics and total amounts along with GIS data to develop water quantity amounts, Nowak determined that urban vegetation has both direct and indirect effects on air quality, carbon sequestration, stream flows, and water quality. Trees directly lower urban temperatures by providing shade while indirectly store carbon in their leaves; the larger and healthier the tree, the more shade it can provide and the more carbon it can store. Likewise, urban trees directly intercept rainfall to transpire water and indirectly filter the runoff to increase the quality of the water. Using this resulting information, policies should be enacted to improve the quality of urban forests, which should positively affect environmental and social environments of cities.

Kilberg, Martin, & Bauer (2012) of the University of Minnesota explains numerous reasons as to importance of urban tree canopy cover. For the Minneapolis, St. Paul, and Woodbury regions, they want to promote stormwater management, improving the water and air supply quantitatively and qualitatively, energy conservation, raising property values, and enhancing community pride and vitality. This study delves into more detail on the methodologies used to derive urban tree canopy cover, which I discuss more in depth in the Methodology section below.

The contract between CGIS, CQGRD, and the City of Atlanta describes cities' need of urban tree coverage with specific initial focus on Atlanta's environmental and aesthetic factors. The contract lists off nearly every single factor with the exception of the three socioeconomic sub factors, compared to the fourteen others. Along with the previously mentioned environmental benefits that urban trees provide, including reducing the urban heat island effect and providing wildlife habitat, CGIS & CQGRD discuss Atlanta's unique watershed characteristics. Riparian trees (trees adjacent to creeks, rivers, and other waterways) make up much of the city's tree population because of the numerous watersheds and stream origin inside the city limits. Riparian trees act as not only a filtration device to help maintain the health of the city's waterways but also as a wildlife habitat. Protection of our watersheds is imperative for our drinking water quality. Even though this report does not specifically state socioeconomic benefits, water quality is indirectly related to community health. In particular, "[w]atershed protection is especially important in Atlanta where 98 percent of the region's drinking water is from surface water. Non-point source pollution (stormwater runoff) is the leading cause of water quality problems, even more than the point source pollution associated with industrial activities" (CGIS, & CQGRD, 2012, p. 2). The benefits of urban tree canopy coverage aid the watersheds both in filtration and stormwater runoff catchment.

Once an inventory is calculated for the City of Atlanta, the city can create policy tools to manage and grow the tree population, riparian and other, inside the city limits, which will enhance the positive externalities that urban vegetation and trees offer. By assessing Atlanta's urban vegetation and tree canopy coverage, subsequent studies can take place. This will allow the city to monitor any changes and act accordingly.

IMAGE 1: DIAGRAM OF FREQUENCY OF LITERATURE REVIEW FINDINGS



The diagram in image 1 above illustrates the frequency with which the ten studies site the beneficial factors of urban vegetation and tree canopy coverage. The larger the circle surrounding the factor, the more often it is discussed among all of the authors. The factors mentioned the most are both in the environmental benefits category: energy savings and air quality. The factors least discussed are both in the urban design benefits category: walkability and crime reduction due to tree placement. The hydrology and socioeconomic categories are rather consistently discussed among the authors, but environmental is an obvious favorite with urban design taking the back burner.

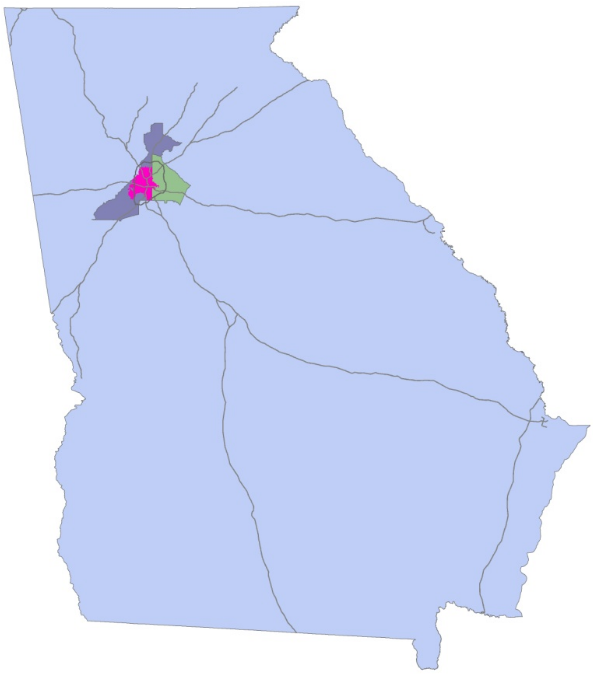
After determining a methodology and results for the City of Atlanta's urban vegetation and tree canopy coverage inventory, I discuss on how these four categories act in the city's current environment.

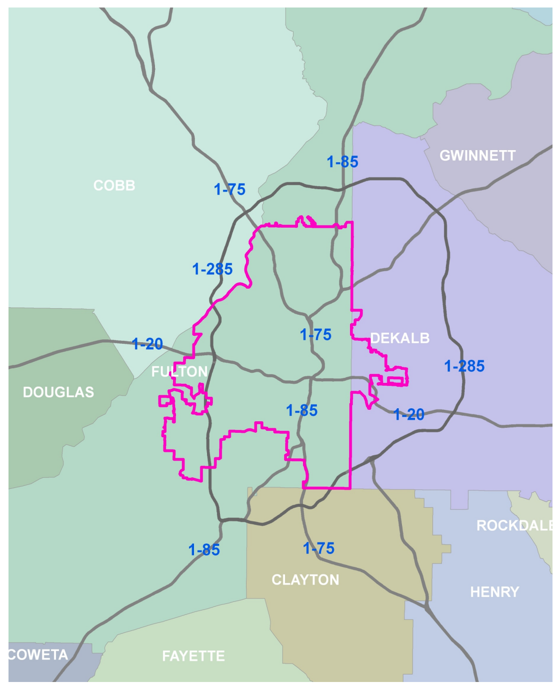
METHODOLOGY

Study Area

Located in the northwestern section of the state of Georgia, the City of Atlanta is roughly 133 square miles and falls mostly into Fulton County, where it is the county seat, with a small eastern portion in Dekalb County (about 125 square miles are in Fulton and about 8 square miles are in Dekalb). This is only about 0.2% of the entire state area. Images 2 and 3 show the city and its counties in reference to the state, the surrounding counties, and major interstates.

IMAGES 2 AND 3: STUDY AREA REFERENCES FOR THE CITY OF ATLANTA IN THE STATE (left) AND FOR THE CITY OF ATLANTA IN REFERENCE TO COUNTIES AND INTERSTATES (right)





According to the U.S. Census Bureau, the 2012 population estimate for the city is 432,427, which is about 4% of the entire state's population. The population density per square mile for the City of Atlanta, though, is much higher than the state of Georgia; a comparison of 18.7 to one. In 2010, the housing units per for the city totaled 224,573, which makes up about 5.5% of the state's total housing supply.

Keeping these statistics in mind, discussed below is the remote sensing methodologies used to determine Atlanta's urban vegetation and tree canopy cover. From the findings, the City of Atlanta can interpolate planning and policy measures appropriate to its physical, political, and social environments.

Calculating tree cover using three methods: NDVI, Unsupervised, and Supervised

The City of Atlanta currently does not have data that quantifies its tree population even though some have made statements referencing decline in said population. In hopes of limiting generalizations of the metro area's tree base, the city obtained Quickbird satellite imagery from October 2008 and is proceeding with remote sensing techniques to classify land cover within the city limits with a concentration on identifying its urban vegetation tree canopy coverage. A review of some literature discusses methodologies to aid in the classification process.

Barnoaiea's (2010) article is based on a study located in the Vanatori Neamt Natural Park in the North East of Romania. It compared IKONOS 2 satellite imagery and aerial imagery of the forest. Both of the imagery is orthorectified and georeferenced in the Land Parcel Identification System (LPIS). For the satellite imagery, the separate spectral bands were merged with the panchromatic via ERDAS IMAGINE's resolution merge function, which produced an image with a 1 meter resolution. As for the aerial imagery, the sample plot is 1 hectare. The crowns of the trees were measured. A canopy cover index was "measured on the image by applying a rectangular network of 100 points over the position of the sample plot…" (Barnoaiea, 2010, p. 242). The aerial imagery was put into ArcGIS where the tree crowns were outlined and then represented as polygons, which produces the crown diameters. The crown diameters can then be compared to the canopy cover index, which represents the density of the stand. The study also compared these two datasets to ground data.

Barnoaiea (2010) analyzed the validity of the findings based on three viewpoints: tree level analysis, sample plot level analysis, and stand level analysis. Tree level analysis uses crown diameter, the position of the trees, and the image pixel. One difficulty with this level of analysis is that the upper tree crowns can cover and disguise the lower tree crowns. For sample plot level analysis, the comparison, via plotting, of data is between the average data from the ground and from the IKONOS 2 images. The main problem the researchers found during this analysis is difficulty in identifying the different species of trees shown in the satellite imagery. The last comparison, stand level analysis, compared four different stands using only ground data. The obvious problem in this analysis type is that one must generalize based on sample data.

Overall, the study favored the IKONOS 2 imagery over the aerial imagery. However, shortcomings were listed for both. The satellite imagery underestimated the amount of trees because of the upper crowns obscuring the view of the lower. The aerial imagery's main issue was high off-nadir angle that occurred during the flights. This is one of the main takeaways from this source, that satellite imagery is preferable when dealing with larger areas, which applies to the over 100 square miles that make up the City of Atlanta. Another takeaway is that using ground data observation is a good way to back up remote sensing techniques. For obtaining tree canopy coverage data for the City of Atlanta, no geocoded ground data is gathered because of the intense amount of time this takes. Furthermore, Atlanta needs a methodology that is easily and quickly replicable, which makes ground data even more inappropriate.

Chanussot, Benediktsson, & Fauvel (2006) put forth a methodology that consists of two sections: feature extraction and classification. From IKONOS imagery, they conducted their two-step classification procedure, which includes large buildings, houses, open areas, large roads, streets, and shadows. The feature extraction step is based on granulometries, which is believed would help with classification efforts in urban areas specifically as opposed to rural areas. Morphological filters are used to create a DMP, or differential morphological profile. This gives the spectrum of each pixel a pattern. The classification step two will be based on a fuzzy interpretation of the possibilistic model using the 16-dimensional vector that the DMP gives each pixel. The feature extraction is applicable to Atlanta's methodology. I use the NDVI process to extract a subset of the satellite imagery, which makes it easier to classify only vegetation, rather than every land cover type. The fuzzy theory is applicable, as well.

After classification, a fuzzy convolve process helps to correct incorrectly classed pixels by using the land cover type that is most common surrounding type.

Cadenasso, Pickett, & Schwarz (2007) note that "[f]uzzy sets theory is the appropriate frame to handle imprecise or uncertain information" given by the DMP because the objects in the imagery do not have perfectly sharp edges (p. 41). Furthermore, it is hard to put strict lines of definition onto land cover types; when does small become large; when does high contrast become low contrast. To remedy this, the authors propose using possibility distributions. In this way, each possible class will have a range that an object will definitely fall into; for instance, a large building has a value of 15 and above and anything that's a 9 or below is a small building. The harder to determine points in the middle are then ranked by likelihood of class. A value of 14 would be ranked closer to large building while a value of 10 would be ranked closer to a smaller building. However, "[s]ince the clores of the different possibility distributions are not necessarily disjoint, one pixel can be considered as possibly belonging to several different classes" (Cadenasso, Pickett, & Schwarz, 2007, p. 42). Contrast now comes into play in the classification process. Different types of objects are given different degrees of contrast. For instance, a shadow can have a much higher contrast possibility than a road. After this step, the object size and contrast information are concatenated to pick the class of land cover. Overall, the fuzzy interpretation of the DMP and the possibilistic model did not account for 100 percent accuracy in land cover classification, but it increased the accuracy. Like many other studies have stated, the accuracy could be greatly increased with expert knowledge of the area.

In another article, Fauvel, Chanussot, & Benediktsson (2006) address the need for a more automated algorithm for classifying urban land cover. Currently, there is no classification methodology that outperforms another. Thus, the authors propose using multiple aspects from various methodologies, which they call decision fusion. It is "defined as the process of fusing information from several individual data sources after each data source has undergone a preliminary classification" (p. 2828). This methodology is based on the fuzzy sets and possibility theory. They specifically use IKONOS imagery with morphological filters for feature extraction. The classification decision is made after both models are run in order to achieve a higher rate of accuracy. If one method's classification is wrong, the fusion process allows for correction.

Three different classification combinations are accounted for: conjunctive combination, disjunctive combination, and compromise combination. Conjunctive combination refers to sources with high conflict, disjunctive combination refers to sources with low conflict, and compromise combination refers to sources with sources with only partial conflict. Source reliability, however, should always be taken into account. Contextual dependent operators should be implemented to remedy all three types of source combination.

Next, a confidence level is assessed via pointwise accuracy, global accuracy, and a combination operator. Pointwise measures the reliability of a given pixel, global measures reliability is based on prior knowledge of how well a classifier has performed in the past, and combination operators normalize global measures for a local area for decision fusion.

Fauvel, Chanussot, & Benediktsson (2006) propose a fusion scheme that creates individual fuzzy sets for each class in each source. Then, the degree of fuzziness is computed for each fuzzy set and normalized with a previously determined factor. The contextual dependent operator is then applied, and the image is classified based on the "highest resulting membership degree" (p. 2833). In practice, the fuzzy classifying methodology worked best for the building, vegetation, and shadow classes, while a neural network classifier worked better for streets and roads. Overall, the authors state that, even though they only used two types of classification methodologies in their decision fusion, more types of classification methodologies could be beneficial.

Moran (2010) uses Quickbird imagery from June, 2008, in determining land cover of a relatively the new urban environment of Lucas do Rio Verde, Mato Grosso State, Brazil. Similarly to other studies, shadows from buildings and trees hinder the classification process. In classifying, the author uses maximum likelihood classifier (MLC), extraction and classification of homogenous objects (ECHO), and segmentation-based classification to determine the best methodology for generating urban tree canopy inventories. MLC uses training samples to infer a pixel's value based on its relative location to the sample points. The ECHO method takes data from both spectral and spatial observations and fills in pixel values based on a specific aggregation of the data. The segmentation-based classification process determines pixels with similar values and spatially connects them; the final step in this segmentation method includes an accuracy assessment after classification. In comparing the three methods' accuracy assessments, the segmentation-based method increased correct classification by 12.7 percent. However, this study had problems with shadowing from buildings and trees, which made the accuracy levels fall a bit.

In reference to land cover classification categories, Dwyer & Miller (1999) use three land cover classifications, tree canopy, grass/herbaceous, and impervious surface, along with land use information to conduct an energy savings analysis. The study applied intense field data, including trunk diameter, species, and total height, to determine individual trees' shade qualities, which is directly related to this energy savings study.

Lastly, in a City Council Briefing for the City of Dallas in 2009 set out to determine the city's urban tree canopy and follow-up steps to take to enhance urban vegetation. The authors delineate a "roadmap" for Dallas that will illustrate where trees are missing, where trees can be planted, and finally the best place to plant trees. In determining the best land for tree planting, the city looks at location, land use type, and hot spot data, which refers to the areas that need the environmental benefits of urban trees the most. The city found that the current urban tree canopy coverage for Dallas is 8 percent, but they have the potential for 30 percent coverage. The briefing then breaks the city down by different geographies, including land use types, neighborhoods, and watersheds, in order to aid in planning and policy implications. The intent of this project is to not only to increase the health of the City of Dallas but also to serve as a model for the region's urban vegetation maintenance and management.

Whether the above studies' focus are more on tree classification or on urban land cover classification, useful methodologies are derived, which are beneficial to the task of quantifying the City of Atlanta's urban vegetation and tree canopy coverage. One of the main ideas derived from these studies is that of multiple types of pixel classification. In Atlanta's case, we will use three methodologies to achieve two classifications. The first classification utilizes the NDVI extraction, or segmentation, and performing a supervised classification on that subset. The second classification process does not use a subset image; rather it is an unsupervised classification on the entire city as a whole.

Supervised classifications are superior if the user has great knowledge of the area. In this case, we do have a great knowledge of the ground environments of the City of Atlanta. In congruence with knowing the area, the NDVI process assumes a certain area that is vegetated. The assumption that the user knows the ground environment and the assumption that the NDVI process knows the vegetation land cover go hand-in-hand. The unsupervised classification process assumes that the user does not have great knowledge of the ground environment. Thus, in this case, the process is performed blindly, or without the subset extrapolated from the NDVI process. In other words, the supervised classification is human or user defined classes while the unsupervised classification is computer defined classes.

The literature suggests many types of fuzzy classifications, which help to correct misclassed pixels, and an accuracy assessment compared to a reference image. After the two classifications, each of the supervised and unsupervised results follow the same remaining processes in this order: recode, fuzzy convolve, clump, eliminate, and an accuracy assessment. The fuzzy convolve, clump, and eliminate processes are all types of fuzzy classifications. The data sources and these processes, along with the recode and accuracy assessment are detailed in the following sections.

Data Sources

IMAGE 4: OF COLOR MISMATCH

The City of Atlanta obtained Quickbird satellite imagery from October, 2008. This is a leaf-on time of year, meaning that all living trees are accounted for from the satellite image; the leaves are still on the trees making them identifiable from an aerial perspective. More specifically, the Quickbird imagery has 4 bands (R, B, G, and near-infrared), 11 bit data, and a two foot resolution. The city's satellite data originated as seven separate images. Originally, we attempted to mosaic the seven images together for analysis purposes. However, the true colors only matched up between two of the seven images, leaving us to analyze six images total. This is necessary to maintain the integrity of actual land cover. A broad classification of the same classes that have different pixel values will result in a skewed outcome.

The color mismatch between the seven original images is illustrated in image 4.

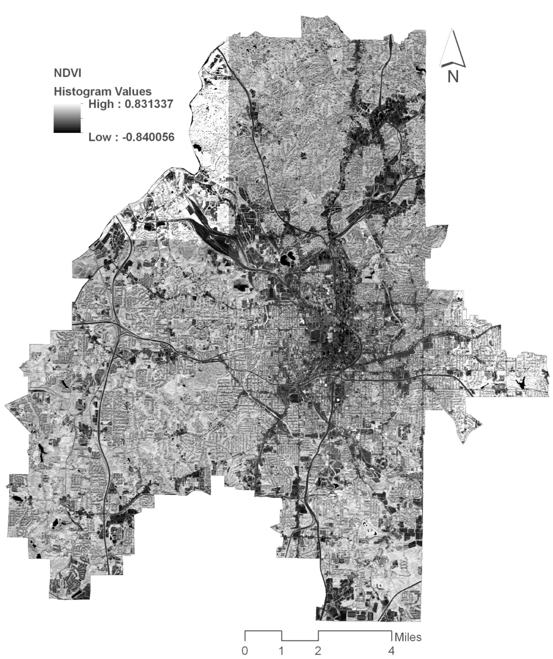
The vector files used in analysis are provided by the City of Atlanta, the Atlanta Regional Commission, and the U. S. Census Bureau. The Census Bureau is the source for all demographic data as well.

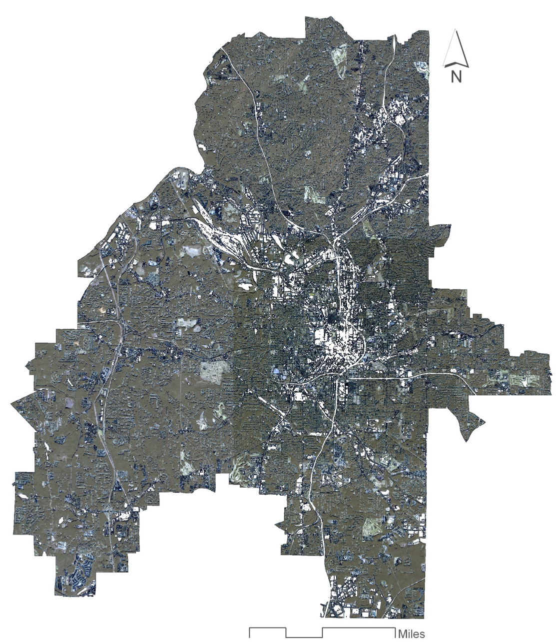
User-Defined Classification Process

NDVI

To determine the amount of urban vegetation for the City of Atlanta, I analyzed the 2008 Quickbird imagery in the ERDAS IMAGINE remote sensing software, in which I performed the Normalized Vegetation Difference Vegetation Index (NDVI) function to determine vegetative land cover as opposed to other land cover, including but not limited to impervious surfaces, water, and bare ground. NDVI refers to the ratio of absorbed near infrared and visible light to reflected near infrared and visible light that a satellite sensor detects. The index ranges from negative one to positive one (-1, 1). If the NDVI amount is between negative one and zero (-1, 0), the land cover is not vegetation. If the NDVI amount is between zero and positive one (0, 1), the land cover is vegetated (USGS, 2010). Images 5 and 6 show the NDVI initial outcome and the subset of the original raw images, respectively. Image 7 shows a zoomed-in view of the NDVI subset image.

IMAGES 5 & 6: INITIAL NDVI OUTCOME/NDVI SUBSET OF THE ORIGINAL RAW IMAGES (pixels with a positive histogram value)

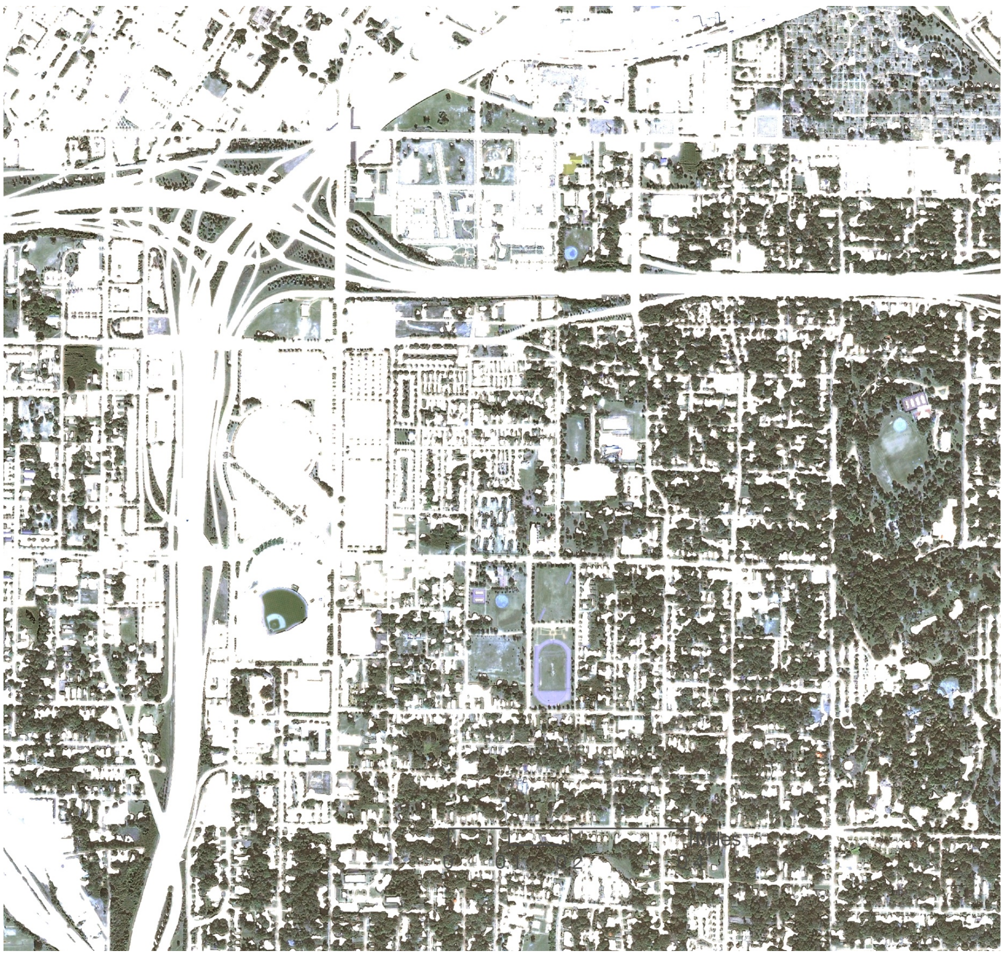




This step allows for total urban vegetation as well as being a subset for the supervised classification process. Overall vegetation, which includes grass and bare ground, is important along with tree canopy coverage for numerous reasons, including stormwater runoff characteristics. As mentioned in the Chapter 1, differentiation in land cover and land use types is necessary in calculating runoff coefficients and the quantity and quality of stormwater.

Different types of vegetation cannot be determined from this index, but the health of vegetation can. For the sake of this analysis, though, I focus on the presence of vegetation alone and its amounts, not its health. From this analysis, the supervised classification is done.

IMAGE 7: NDVI SUBSET OF THE ORIGINAL RAW IMAGES: ZOOM-IN



Supervised Classification

The supervised classification process uses human, or user, defined classes to determine land cover. This process is best utilized when the user knows the ground environment well. Because I work and reside in the Atlanta and am very familiar with the city, I am able to complete the supervised classification process.

In order to complete this process, I start by creating polygon area of interest (AOI) files. There are two main ways to accomplish this. The first is by the grow polygon function (image 8); by selecting an initial one or a few pixels, the computer grows a complex polygon that includes all of the connecting pixels of the same value. This function is beneficial in creating a polygon including a large area of similar pixels while excluding non-matching pixels. The second AOI polygon function is the draw polygon (image). This creates a solely user defined polygon, generally with much less intricacy than the grow function. The benefit of the polygon function, though, is that the user can include pixels of very different values that represent the same land cover. In the case of Atlanta's study, this is very beneficial because taller objects, trees in particular, often cast a shadow. When drawing polygons rather than growing, I can include shadowed pixels in a polygon that a grow function would not recognize. Using a combination of both of the AOI polygon creation functions, I can create a comprehensive set of polygons to create a signature file, which is the next step in the supervised classification process.

IMAGE 8: AOI FUNCTION: GROW POLYGON

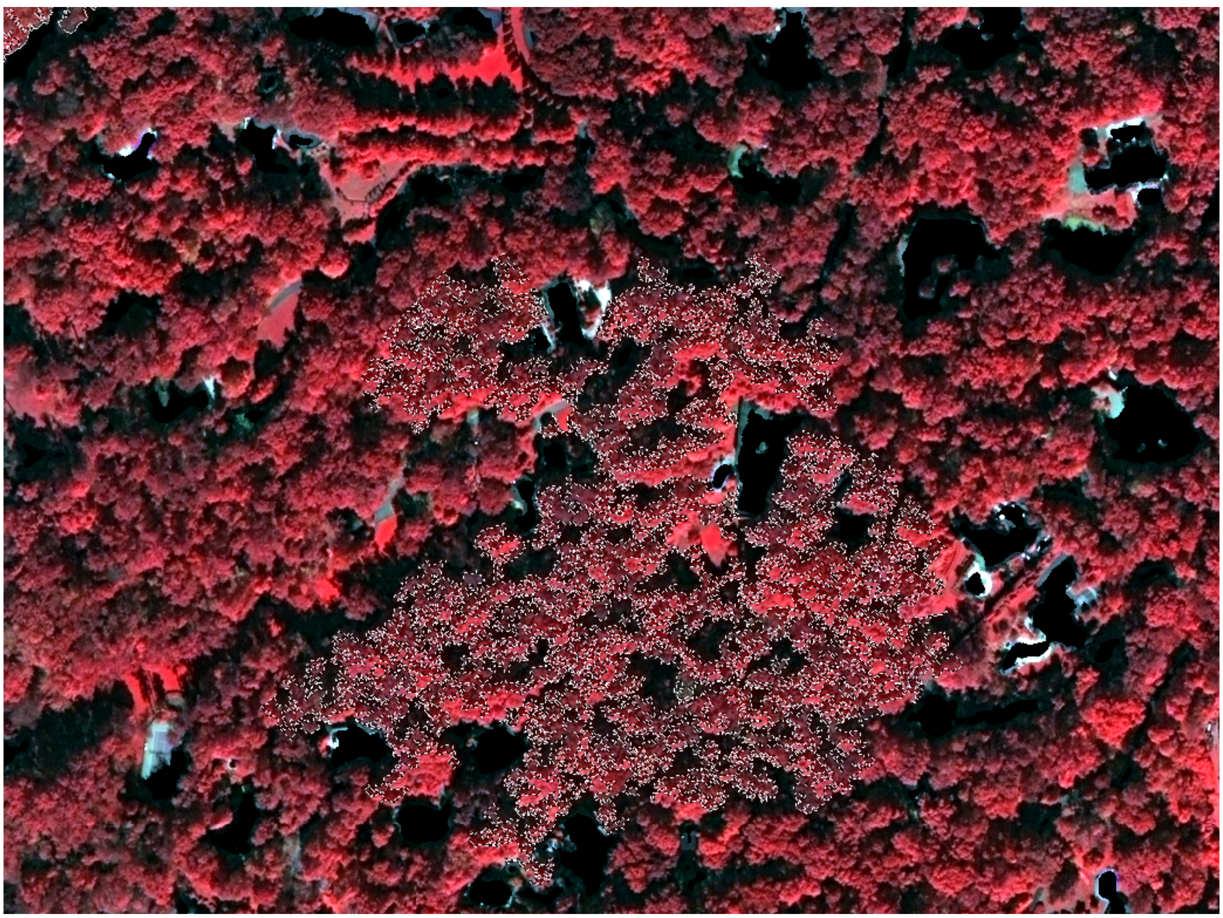
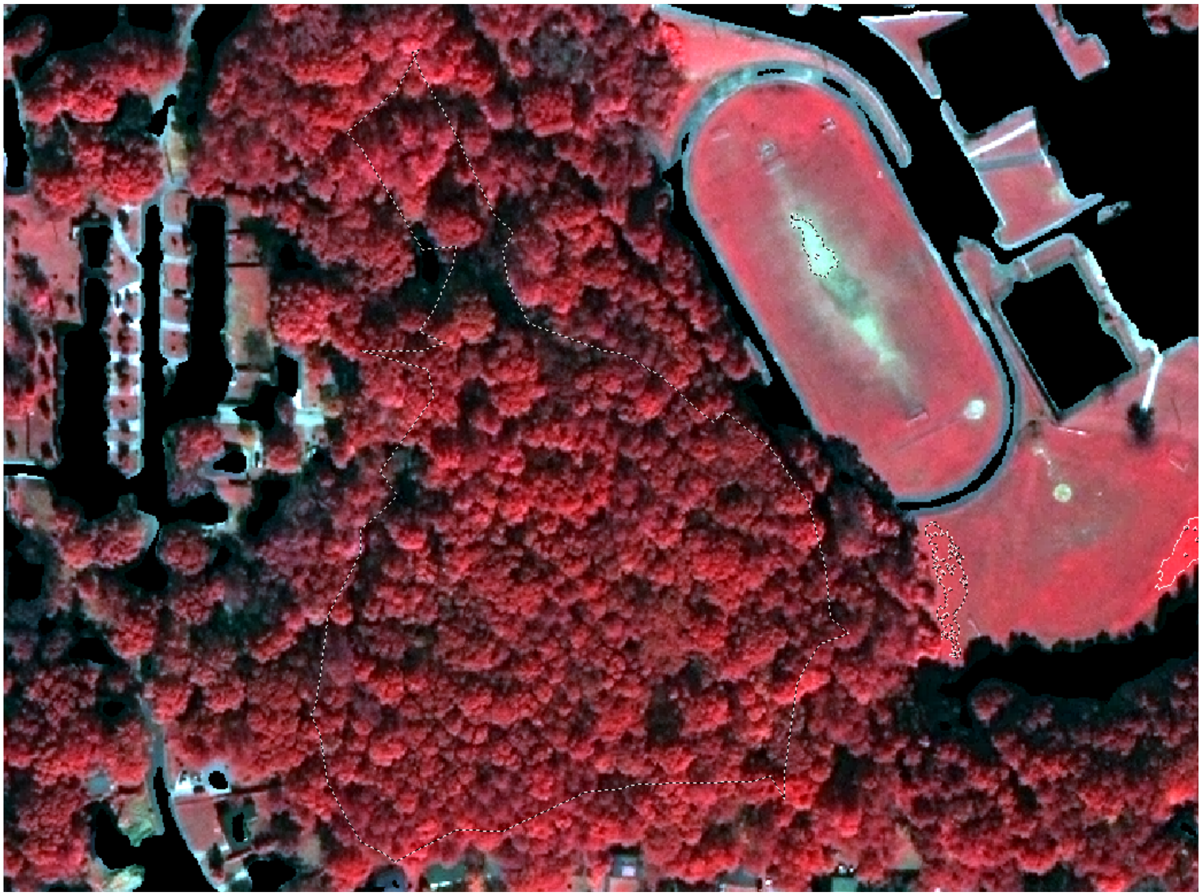


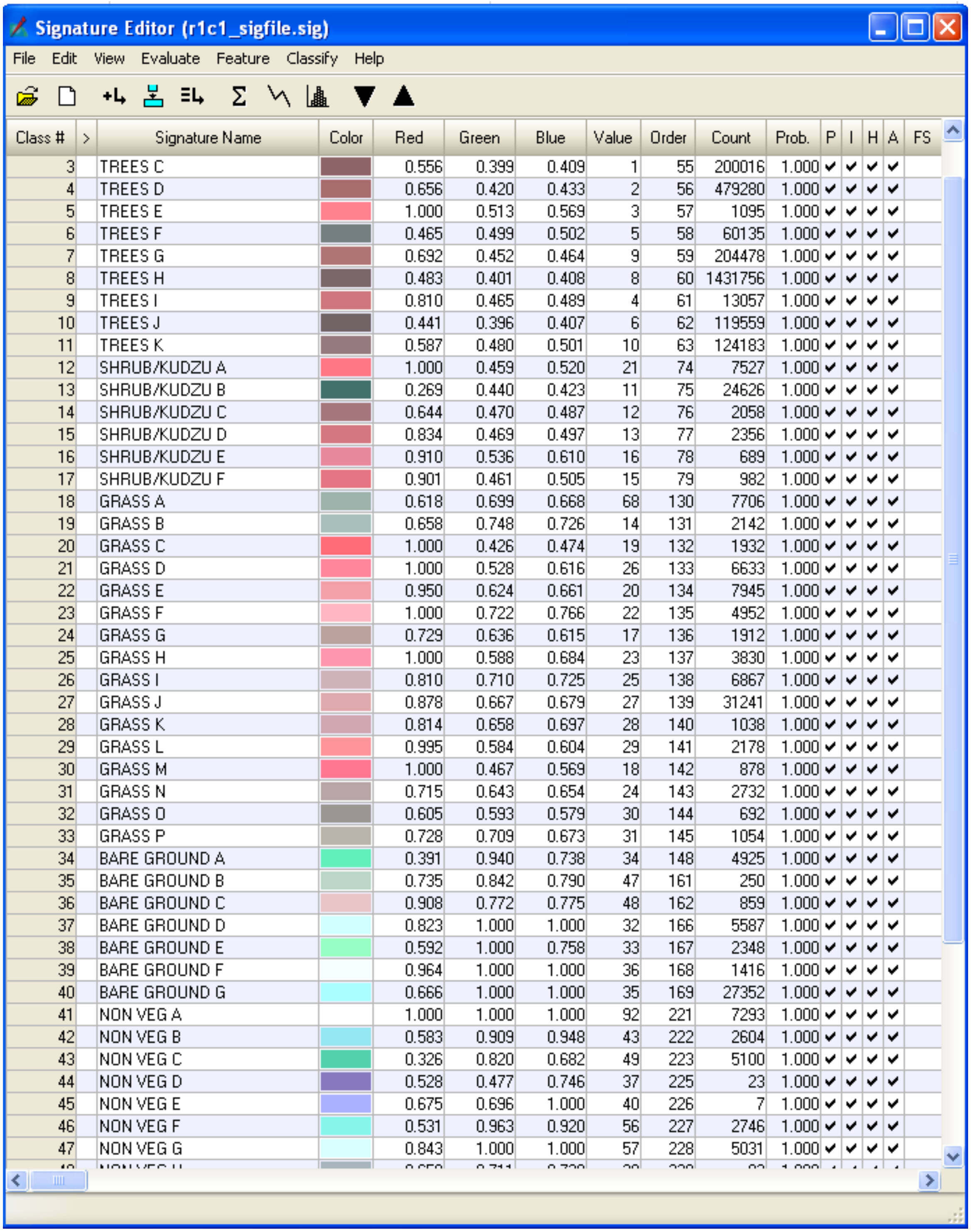
IMAGE 9: AOI FUNCTION: DRAW POLYGON



The signature file uses the grown and drawn polygons in the AOI file to outline land cover classes. As seen in image 10, I created numerous classes per land cover category in order to account for the vastly different color pixels representing in each class. By keeping each class' various colors separated, I maintain every possible color combination for each land cover. For instance, a dark red tree cover (due to shadowing) will not be canceled out by the bright red tree tops directly exposed to sunlight; combining the two would average the pixels' values to only represent the mid-range red of the tree canopy. Because of the great variation of pixel value within all each of the land cover classes and to maintain the validity of the signature files, I have 50 to 100 classes per image.

Images 11 and 12 show the six images' supervised classification and a zoomed-in look respectively.

IMAGE 10: SUPERVISED CLASSIFICATION ATTRIBUTE TABLE



Class #	>	Signature Name	Color	Red	Green	Blue	Value	Order	Count	Prob.	P	I	H	A	FS
3		TREES C		0.556	0.399	0.409	1	55	200016	1.000	✔	✔	✔	✔	
4		TREES D		0.656	0.420	0.433	2	56	479280	1.000	✔	✔	✔	✔	
5		TREES E		1.000	0.513	0.569	3	57	1095	1.000	✔	✔	✔	✔	
6		TREES F		0.465	0.499	0.502	5	58	60135	1.000	✔	✔	✔	✔	
7		TREES G		0.692	0.452	0.464	9	59	204478	1.000	✔	✔	✔	✔	
8		TREES H		0.483	0.401	0.408	8	60	1431756	1.000	✔	✔	✔	✔	
9		TREES I		0.810	0.465	0.489	4	61	13057	1.000	✔	✔	✔	✔	
10		TREES J		0.441	0.396	0.407	6	62	119559	1.000	✔	✔	✔	✔	
11		TREES K		0.587	0.480	0.501	10	63	124183	1.000	✔	✔	✔	✔	
12		SHRUB/KUDZU A		1.000	0.459	0.520	21	74	7527	1.000	✔	✔	✔	✔	
13		SHRUB/KUDZU B		0.269	0.440	0.423	11	75	24626	1.000	✔	✔	✔	✔	
14		SHRUB/KUDZU C		0.644	0.470	0.487	12	76	2058	1.000	✔	✔	✔	✔	
15		SHRUB/KUDZU D		0.834	0.469	0.497	13	77	2356	1.000	✔	✔	✔	✔	
16		SHRUB/KUDZU E		0.910	0.536	0.610	16	78	689	1.000	✔	✔	✔	✔	
17		SHRUB/KUDZU F		0.901	0.461	0.505	15	79	982	1.000	✔	✔	✔	✔	
18		GRASS A		0.618	0.699	0.668	68	130	7706	1.000	✔	✔	✔	✔	
19		GRASS B		0.658	0.748	0.726	14	131	2142	1.000	✔	✔	✔	✔	
20		GRASS C		1.000	0.426	0.474	19	132	1932	1.000	✔	✔	✔	✔	
21		GRASS D		1.000	0.528	0.616	26	133	6633	1.000	✔	✔	✔	✔	
22		GRASS E		0.950	0.624	0.661	20	134	7945	1.000	✔	✔	✔	✔	
23		GRASS F		1.000	0.722	0.766	22	135	4952	1.000	✔	✔	✔	✔	
24		GRASS G		0.729	0.636	0.615	17	136	1912	1.000	✔	✔	✔	✔	
25		GRASS H		1.000	0.588	0.684	23	137	3830	1.000	✔	✔	✔	✔	
26		GRASS I		0.810	0.710	0.725	25	138	6867	1.000	✔	✔	✔	✔	
27		GRASS J		0.878	0.667	0.679	27	139	31241	1.000	✔	✔	✔	✔	
28		GRASS K		0.814	0.658	0.697	28	140	1038	1.000	✔	✔	✔	✔	
29		GRASS L		0.995	0.584	0.604	29	141	2178	1.000	✔	✔	✔	✔	
30		GRASS M		1.000	0.467	0.569	18	142	878	1.000	✔	✔	✔	✔	
31		GRASS N		0.715	0.643	0.654	24	143	2732	1.000	✔	✔	✔	✔	
32		GRASS O		0.605	0.593	0.579	30	144	692	1.000	✔	✔	✔	✔	
33		GRASS P		0.728	0.709	0.673	31	145	1054	1.000	✔	✔	✔	✔	
34		BARE GROUND A		0.391	0.940	0.738	34	148	4925	1.000	✔	✔	✔	✔	
35		BARE GROUND B		0.735	0.842	0.790	47	161	250	1.000	✔	✔	✔	✔	
36		BARE GROUND C		0.908	0.772	0.775	48	162	859	1.000	✔	✔	✔	✔	
37		BARE GROUND D		0.823	1.000	1.000	32	166	5587	1.000	✔	✔	✔	✔	
38		BARE GROUND E		0.592	1.000	0.758	33	167	2348	1.000	✔	✔	✔	✔	
39		BARE GROUND F		0.964	1.000	1.000	36	168	1416	1.000	✔	✔	✔	✔	
40		BARE GROUND G		0.666	1.000	1.000	35	169	27352	1.000	✔	✔	✔	✔	
41		NON VEG A		1.000	1.000	1.000	92	221	7293	1.000	✔	✔	✔	✔	
42		NON VEG B		0.583	0.909	0.948	43	222	2604	1.000	✔	✔	✔	✔	
43		NON VEG C		0.326	0.820	0.682	49	223	5100	1.000	✔	✔	✔	✔	
44		NON VEG D		0.528	0.477	0.746	37	225	23	1.000	✔	✔	✔	✔	
45		NON VEG E		0.675	0.696	1.000	40	226	7	1.000	✔	✔	✔	✔	
46		NON VEG F		0.531	0.963	0.920	56	227	2746	1.000	✔	✔	✔	✔	
47		NON VEG G		0.843	1.000	1.000	57	228	5031	1.000	✔	✔	✔	✔	

IMAGE 11: SIX IMAGE COMPOSITE OF THE SUPERVISED CLASSIFICATION

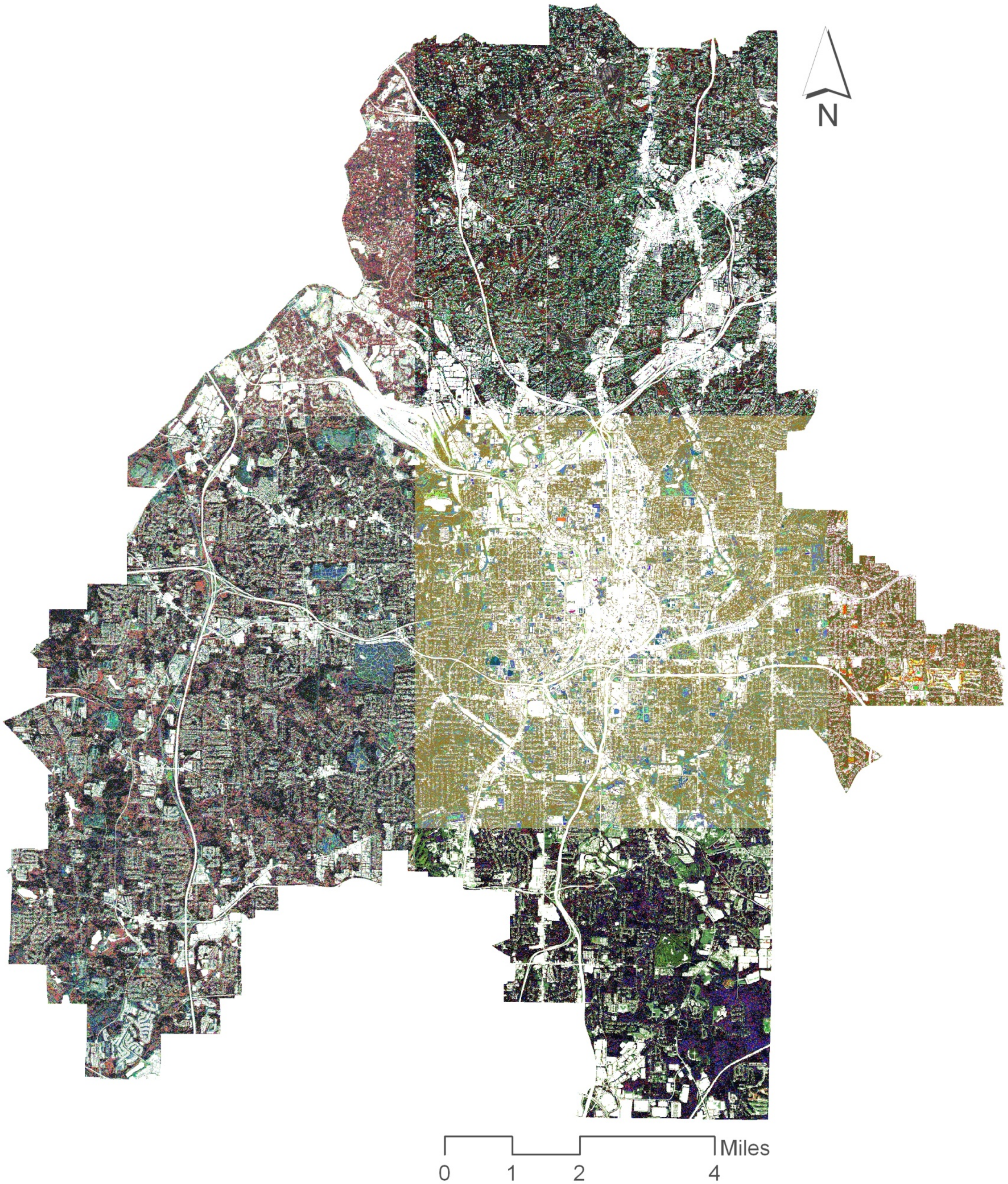
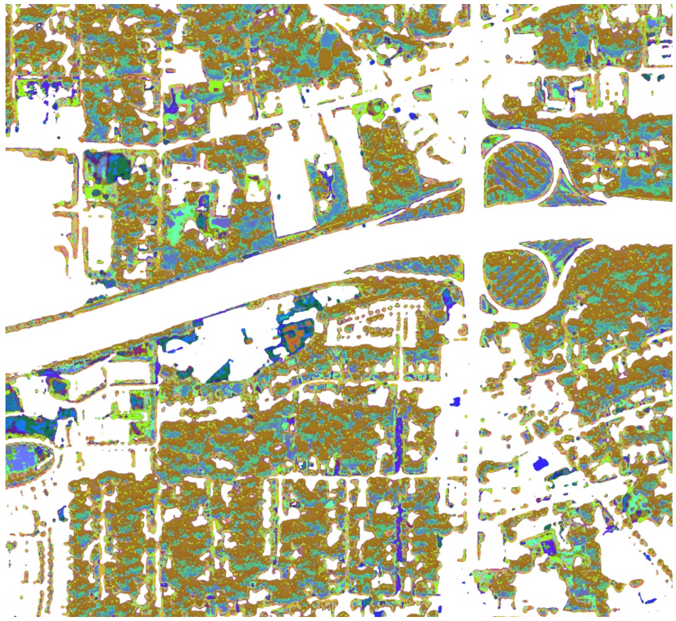


IMAGE 12: SUPERVISED CLASSIFICATION ZOOM-IN



Computer-Defined Classification Process

Unlike the user-defined classification process that subsets the vegetation land cover as a whole from the raw images, the computer-defined classification process essentially executes the process blindly. Instead of the two steps, as is the case with the human-defined classification detailed above, this process only has one step, the unsupervised

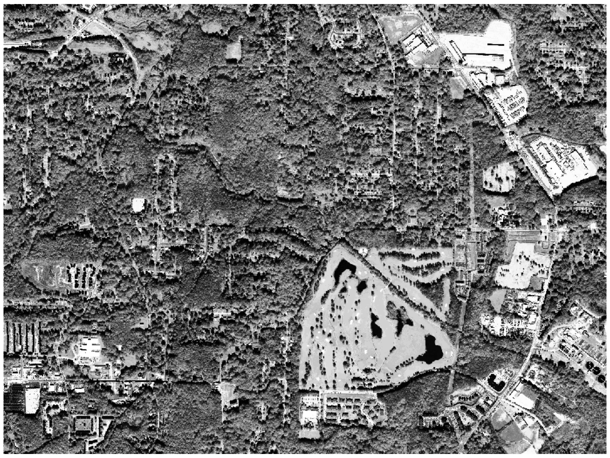
Unsupervised

The unsupervised classification process maintains that the user does not have a great knowledge of the ground environment of the study area. To reiterate, because of this assumption, we did not use the NDVI subset in the classification process. Rather, we performed the unsupervised classification blindly. With a given class amount input of 100 classes, the computer defines 100 varying pixel values ranging from white to black. By highlighting each of the 100 classes separately and comparing these cells to a true color image, we delineated each class as one of four land cover categories: trees, grass, non-vegetation, and shadow; the shadow category is added in the unsupervised classification due to the non-user defined but rather computer defined signatures.

Images 12 and 13 show a zoom-in of the initial unsupervised classification output. The next images, 14 and 15, show the beginning of the class-defining processes, which includes six of the pixels defined as the grass land cover. Last, images 16 and 17 show another zoom-in portion of the city with all of its pixels assigned to a land cover category; the dark green represents trees, the light green represents grass, the light gray represents non-vegetation, and the orange represents the shadow class.

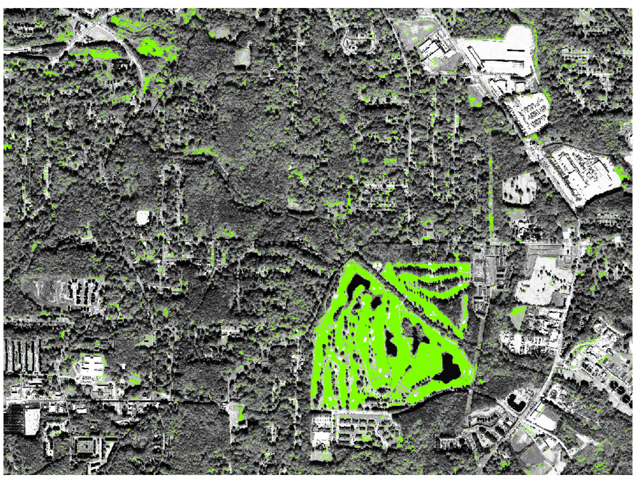
Image 18 is the entirety of the six images together, classified using the unsupervised method.

IMAGES 12 & 13: INITIAL UNSUPERVISED CLASSIFICATION OUTPUT AND ATTRIBUTE TABLE (respectively)



22	1193355		0.22	0.22	0.22	1	Class 22
23	880426		0.23	0.23	0.23	1	Class 23
24	1098417		0.24	0.24	0.24	1	Class 24
25	930449		0.25	0.25	0.25	1	Class 25
26	1160111		0.26	0.26	0.26	1	Class 26
27	1183333		0.27	0.27	0.27	1	Class 27
28	1050750		0.28	0.28	0.28	1	Class 28
29	745468		0.29	0.29	0.29	1	Class 29
30	2462618		0.3	0.3	0.3	1	Class 30
31	676820		0.31	0.31	0.31	1	Class 31
32	842199		0.32	0.32	0.32	1	Class 32
33	1162214		0.33	0.33	0.33	1	Class 33
34	1868726		0.34	0.34	0.34	1	Class 34
35	573529		0.35	0.35	0.35	1	Class 35
36	1101356		0.36	0.36	0.36	1	Class 36
37	838319		0.37	0.37	0.37	1	Class 37
38	1423205		0.38	0.38	0.38	1	Class 38
39	1560530		0.39	0.39	0.39	1	Class 39
40	1007844		0.4	0.4	0.4	1	Class 40
41	1054432		0.41	0.41	0.41	1	Class 41
42	1153621		0.42	0.42	0.42	1	Class 42
43	1053009		0.43	0.43	0.43	1	Class 43
44	1422248		0.44	0.44	0.44	1	Class 44
45	608448		0.45	0.45	0.45	1	Class 45
46	1022485		0.46	0.46	0.46	1	Class 46
47	1244284		0.47	0.47	0.47	1	Class 47
48	742854		0.48	0.48	0.48	1	Class 48
49	477085		0.49	0.49	0.49	1	Class 49
50	982309		0.5	0.5	0.5	1	Class 50
51	1511938		0.51	0.51	0.51	1	Class 51
52	1721631		0.52	0.52	0.52	1	Class 52
53	1213351		0.53	0.53	0.53	1	Class 53
54	1237246		0.54	0.54	0.54	1	Class 54
55	1106869		0.55	0.55	0.55	1	Class 55
56	1330607		0.56	0.56	0.56	1	Class 56
57	573914		0.57	0.57	0.57	1	Class 57
58	3162437		0.58	0.58	0.58	1	Class 58
59	1256841		0.59	0.59	0.59	1	Class 59
60	1310275		0.6	0.6	0.6	1	Class 60
61	734502		0.61	0.61	0.61	1	Class 61
62	1061190		0.62	0.62	0.62	1	Class 62
63	1267639		0.63	0.63	0.63	1	Class 63
64	1140877		0.64	0.64	0.64	1	Class 64
65	1434409		0.65	0.65	0.65	1	Class 65
66	1072177		0.66	0.66	0.66	1	Class 66
67	1080867		0.67	0.67	0.67	1	Class 67
68	555828		0.68	0.68	0.68	1	Class 68
69	461917		0.69	0.69	0.69	1	Class 69
70	1268707		0.7	0.7	0.7	1	Class 70

IMAGES 14 & 15: BEGINNING OF CLASS DEFINITION FOR UNSUPERVISED CLASSIFICATION AND ATTRIBUTE TABLE (respectively)

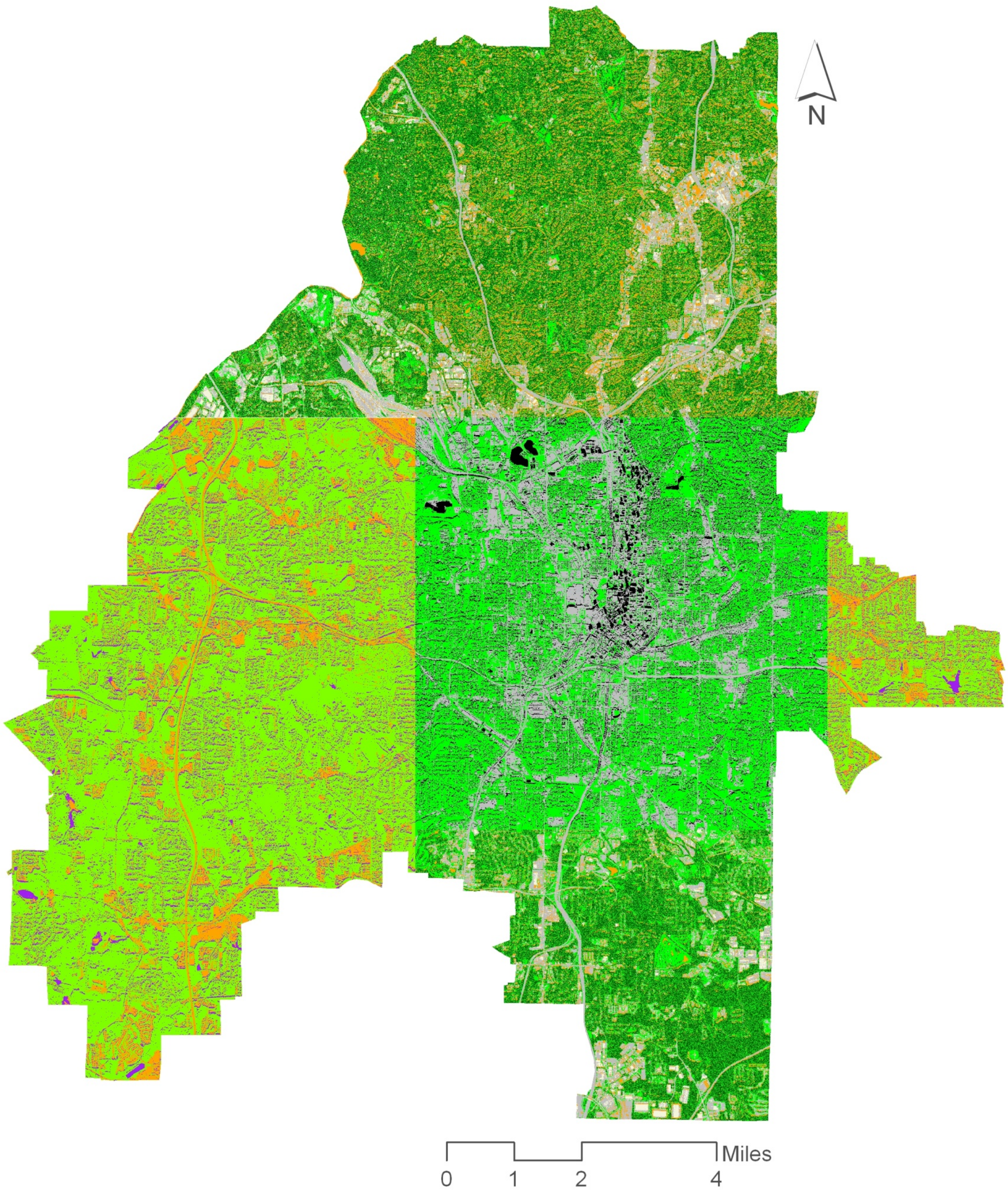


49	477085		0.49	0.49	0.49	1	Class 49
50	982309		0.5	0.5	0.5	1	Class 50
51	1511938		0.51	0.51	0.51	1	Class 51
52	1721631		0.52	0.52	0.52	1	Class 52
53	1213351		0.53	0.53	0.53	1	Class 53
54	1237246		0.54	0.54	0.54	1	Class 54
55	1106869		0.55	0.55	0.55	1	Class 55
56	1330607		0.56	0.56	0.56	1	Class 56
57	573914		0.57	0.57	0.57	1	Class 57
58	3162437		0.58	0.58	0.58	1	Class 58
59	1256841		0.59	0.59	0.59	1	Class 59
60	1310275		0.6	0.6	0.6	1	Class 60
61	734502		0.61	0.61	0.61	1	Class 61
62	1061190		0.62	0.62	0.62	1	Class 62
63	1267639		0.63	0.63	0.63	1	Class 63
64	1140877		0.64	0.64	0.64	1	Class 64
65	1434409		0.65	0.65	0.65	1	Class 65
66	1072177		0.66	0.66	0.66	1	Class 66
67	1080867		0.67	0.67	0.67	1	Class 67
68	555828		0.68	0.68	0.68	1	Class 68
69	461917		0.69	0.69	0.69	1	Class 69
70	1268707		0.7	0.7	0.7	1	Class 70
71	371416		0.71	0.71	0.71	1	Class 71
72	1164265		0.72	0.72	0.72	1	Class 72
73	374406		0.73	0.73	0.73	1	Class 73
74	1041268		0.74	0.74	0.74	1	Class 74
75	1243513		0.75	0.75	0.75	1	Class 75
76	1139101		0.76	0.76	0.76	1	Class 76
77	1060455		0.498039	1	0	1	grass
78	1100875		0.498039	1	0	1	grass
79	587574		0.79	0.79	0.79	1	Class 79
80	612992		0.8	0.8	0.8	1	Class 80
81	687403		0.81	0.81	0.81	1	Class 81
82	813067		0.498039	1	0	1	grass
83	445652		0.83	0.83	0.83	1	Class 83
84	529334		0.84	0.84	0.84	1	Class 84
85	406001		0.498039	1	0	1	grass
86	407099		0.498039	1	0	1	grass
87	492024		0.87	0.87	0.87	1	Class 87
88	206814		0.88	0.88	0.88	1	Class 88
89	496535		0.89	0.89	0.89	1	Class 89
90	294741		0.498039	1	0	1	grass
91	325824		0.91	0.91	0.91	1	Class 91
92	420630		0.92	0.92	0.92	1	Class 92
93	922999		0.93	0.93	0.93	1	Class 93
94	419672		0.94	0.94	0.94	1	Class 94
95	988439		0.95	0.95	0.95	1	Class 95
96	2513545		0.96	0.96	0.96	1	Class 96
97	[illegible]		0.97	0.97	0.97	1	Class 97

IMAGES 16 & 17: FINAL PRODCUT OF CLASS DEFINITION FOR UNSUPERVISED CLASSIFICATION AND ATTRIBUTE TABLE (respectively)

0	[illegible]		0	0	0	0	Unclassified
1	830945		1	0.65	0	1	shadow
2	1117330		1	0.65	0	1	shadow
3	712769		1	0.65	0	1	shadow
4	1049966		1	0.65	0	1	shadow
5	876560		1	0.65	0	1	shadow
6	813425		0.75	0.75	0.75	1	shadow
7	1020090		0.96	0.96	0.86	1	non
8	649596		1	0.65	0	1	shadow
9	699535		0	0.39	0	1	shadow
10	577458		0	0.39	0	1	shadow
11	534617		1	0.65	0	1	shadow
12	577539		1	0.65	0	1	shadow
13	682756		0	0.39	0	1	shadow
14	561713		0	0.39	0	1	shadow
15	788902		0	0.39	0	1	shadow
16	554864		0	1	0	1	veg
17	505643		1	0.65	0	1	shadow
18	604543		0	0.39	0	1	veg
19	722252		0	0.39	0	1	veg
20	393755		0	0.39	0	1	shadow
21	571329		0	0.39	0	1	veg
22	674744		0	0.39	0	1	veg
23	607141		0	0.39	0	1	veg
24	428326		0	0.39	0	1	veg
25	406744		0	0.39	0	1	veg
26	475701		1	0.65	0	1	shadow
27	701695		0	0.39	0	1	veg
28	773689		0.82	0.71	0.55	1	veg
29	414114		0	0.39	0	1	veg
30	379008		0	1	0	1	veg
31	773195		0.75	0.75	0.75	1	veg
32	428694		0	1	0	1	shadow
33	443867		0	0.39	0	1	veg
34	409963		0	1	0	1	veg
35	641127		0	0.39	0	1	veg
36	384743		0.75	0.75	0.75	1	shadow
37	535399		0	1	0	1	veg
38	681637		0	0.39	0	1	veg
39	368643		0	0.39	0	1	veg
40	621875		0	0.39	0	1	veg
41	742005		0	0.39	0	1	veg

IMAGE 18: SIX IMAGE COMPOSITE OF THE SUPERVISED CLASSIFICATION



The remaining steps are performed on both the supervised and unsupervised classification processes.

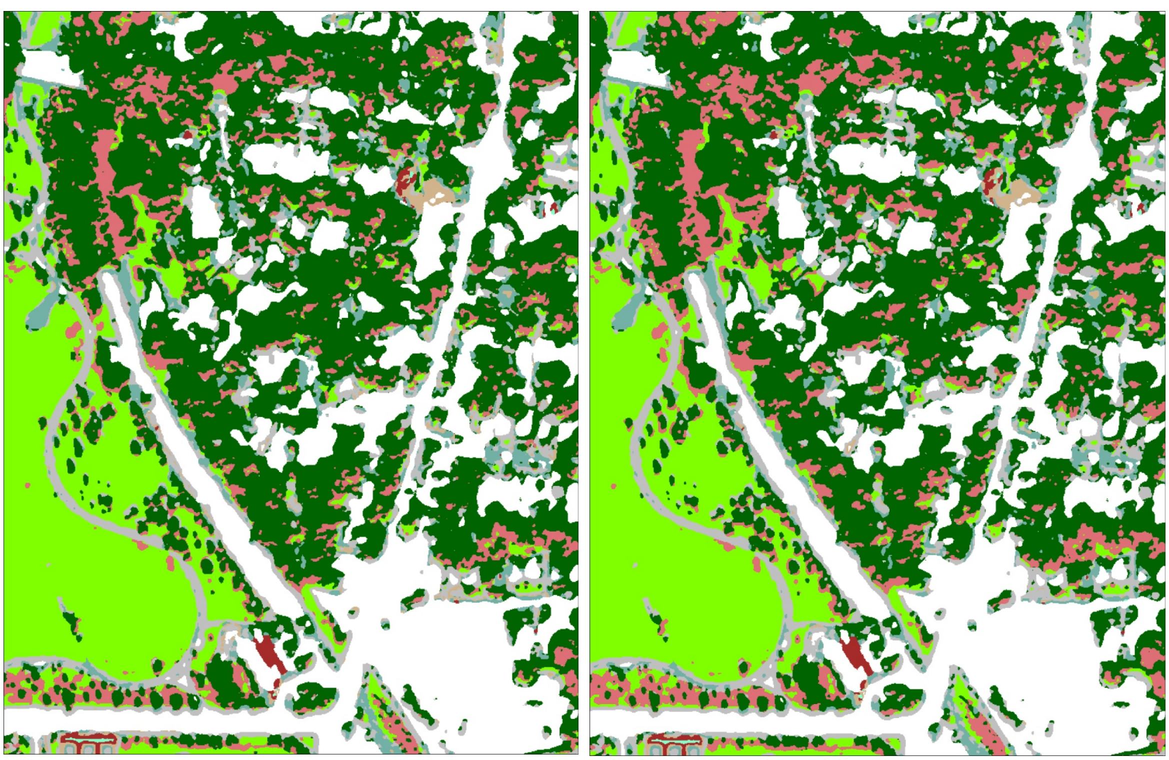
Correction Process

Fuzzy Convolve

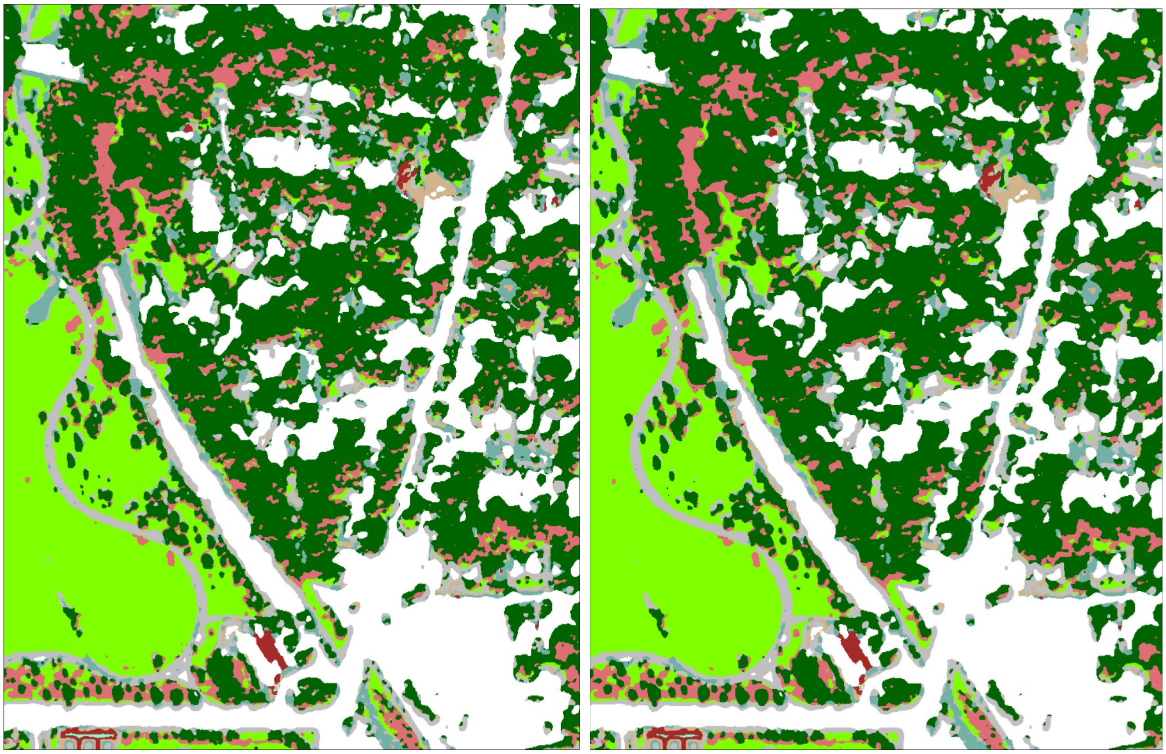
The fuzzy convolve process attempts to remove any remaining isolated pixels in order to smooth out the land cover classes. We experimented with four different settings for the fuzzy convolve, with ranges in the window size (5x5 or 7x7) and in number of classes (2 or 3). The window size refers to the amount of pixels assessed at one time, and the class amount refers to the amount of output infill classes possible in assessment but not the amount of classes possible in the output, which can be as many as are in the original image. Thus, the four possibilities for the fuzzy convolves for each classification is 5x5 (25 pixels) with 2 classes, 5x5 (25 pixels) with 3 classes, 7x7 (49 pixels) with 2 classes, and 7x7 (49 pixels) with 3 classes.

After running the four fuzzy convolve operations for both the supervised and unsupervised classification, we visually compared the results to determine which output is the most accurate for each classification. Most often, the 7x7 with 3 classes output images created the smoothest and most accurate appearing result, however, each image's various classifications can have a different preference. For instance, images 19 through 22 show the supervised classification of the area around the intersection of 10th Street and Monroe Drive, including a sliver of Piedmont Park to the left. The fuzzy convolve with the smoothest and most accurate land cover is image 22, which is the most common 7x7 with 3 class iteration.

IMAGES 19 & 20: 5X5 WINDOW WITH 2 CLASSES/5X5 WINDOW WITH 3 CLASSES



IMAGES 21 & 22: 7X7 WINDOW WITH 2 CLASSES/7X7 WINDOW WITH 3 CLASSES



Recode

The main idea of recoding all of the sub classes, including GRASS A through GRASS P into one consolidated grass class, is to create a more comprehensive class system that compiles the multiple different colors together and form an overall land coverage system. The output images do not appear any different than the non-recoded images, however the attribute table only have three classes for the supervised image, instead of 50 to 100, and four classes for the unsupervised image, instead of 100.

Clump

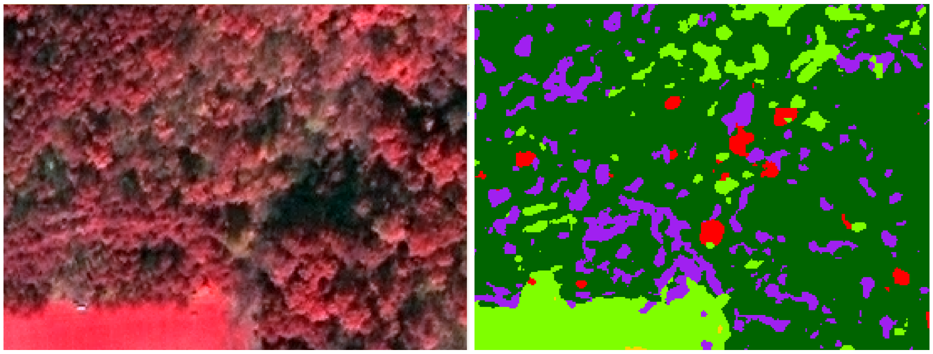
The clump step is a necessary step to accomplish any further image smoothing processes. The clump function identifies all groups, or clumps, of similar pixels. Image 23 shows how every clump output is portrayed, with varying shades of white, gray, and black. The clump outcome acts an in input for the eliminate step, which is explained below.

IMAGE 23: CLUMP OUTPUT

Eliminate

The eliminate function removes groups defined by the clump process that are smaller than a user-specified size and fills in the clump with the land cover of the surrounding class. This is very important in eliminating the missed classed pixels within the tree canopy layer, which is due greatly to the varying pixel colors of the tree canopy image and the shadows caused by the trees. In the clump eliminating process, we experimented with eliminating the minimum size clump (2 pixels) all the way up to 100 pixel clumps. In images 24 through 31 below, a progression is illustrated starting with the raw and recoded images, then showing the results of eliminating a 2 pixel clump, a 6 pixel clump, a 10 pixel clump, a 20 pixel clump, a 50 pixel clump, and finally a 100 pixel clump. After assessing the results of every sized clump elimination, the 100 pixel clump elimination proved to be most beneficial. In other words, this largest clump elimination created the smoothest land cover classification for both the supervised and unsupervised process.

IMAGES 24 & 25: RAW IMAGE; INPUT: RECODE; ELIMINATE 2 PIXELS



IMAGES 26 & 27: ELIMINATE 2 PIXELS; ELIMINATE 6 PIXELS

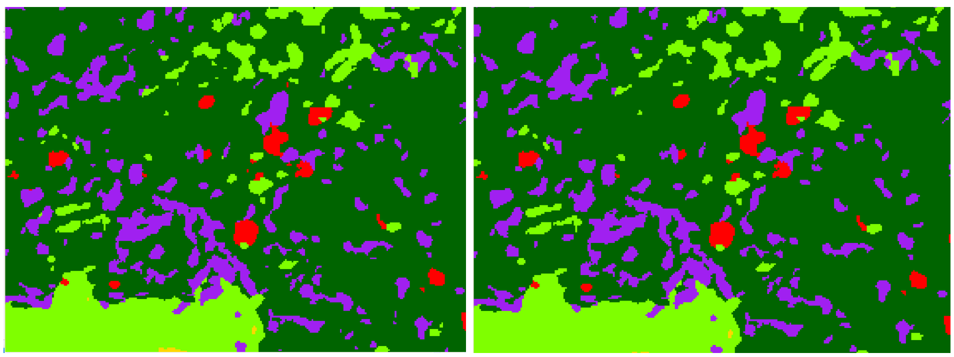


IMAGE 28 & 29: ELIMINATE 10 PIXELS; ELIMINATE 20 PIXELS

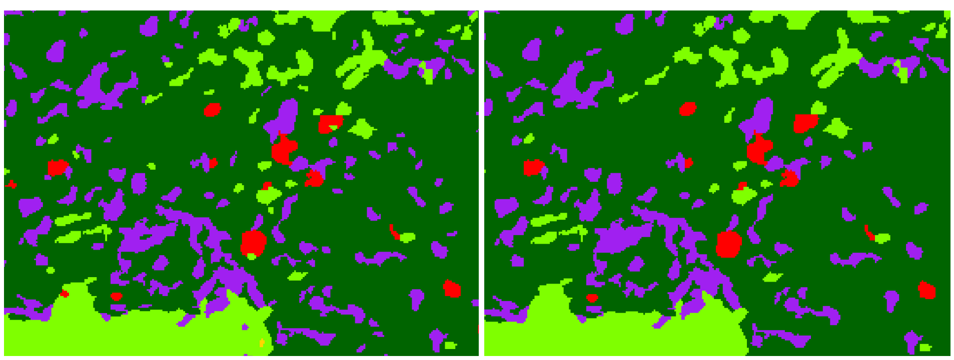
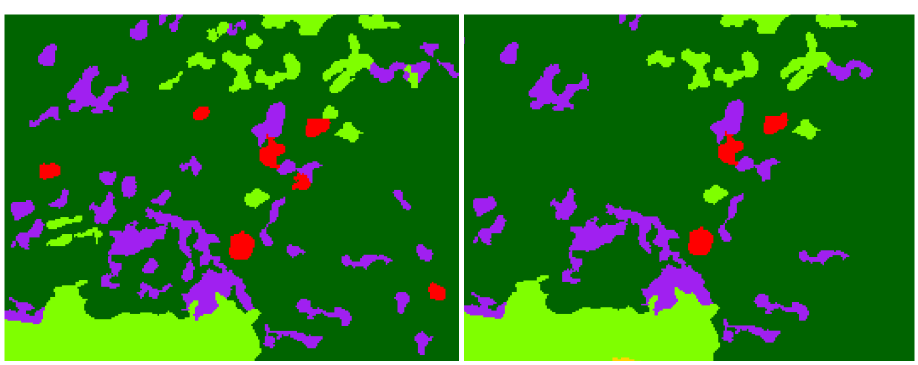


IMAGE 30 & 31: ELIMINATE 50 PIXELS; ELIMINATE 100 PIXELS



Mosaic

Now that all of the six initial images are classified and corrected, they are pieced together in one mosaic image. In this way, an accuracy assessment is easily attainable, as well as further spatial analysis, such as total tree canopy cover. For the final images, the supervised classification is simplified and recoded to four classes: grass, tree, non-vegetation darkly shaded pixels, and non-vegetation lightly shaded pixels. For the unsupervised classification final image, the classes are simplified and recoded to five classes: the same four illustrated in the supervised image along with a shadow class. In order to classify all urban vegetation into two classes, all large shrubbery and bigger amounts of vegetation are classified as trees. Anything smaller than that, including kudzu, is classified as grass. All bare ground is classified as non-vegetation lightly shaded.

Image 32 shows the final mosaic supervised classified image, and image 33 shows the final mosaic unsupervised classified image.

IMAGE 32: FINAL SUPERVISED CLASSIFIED IMAGE

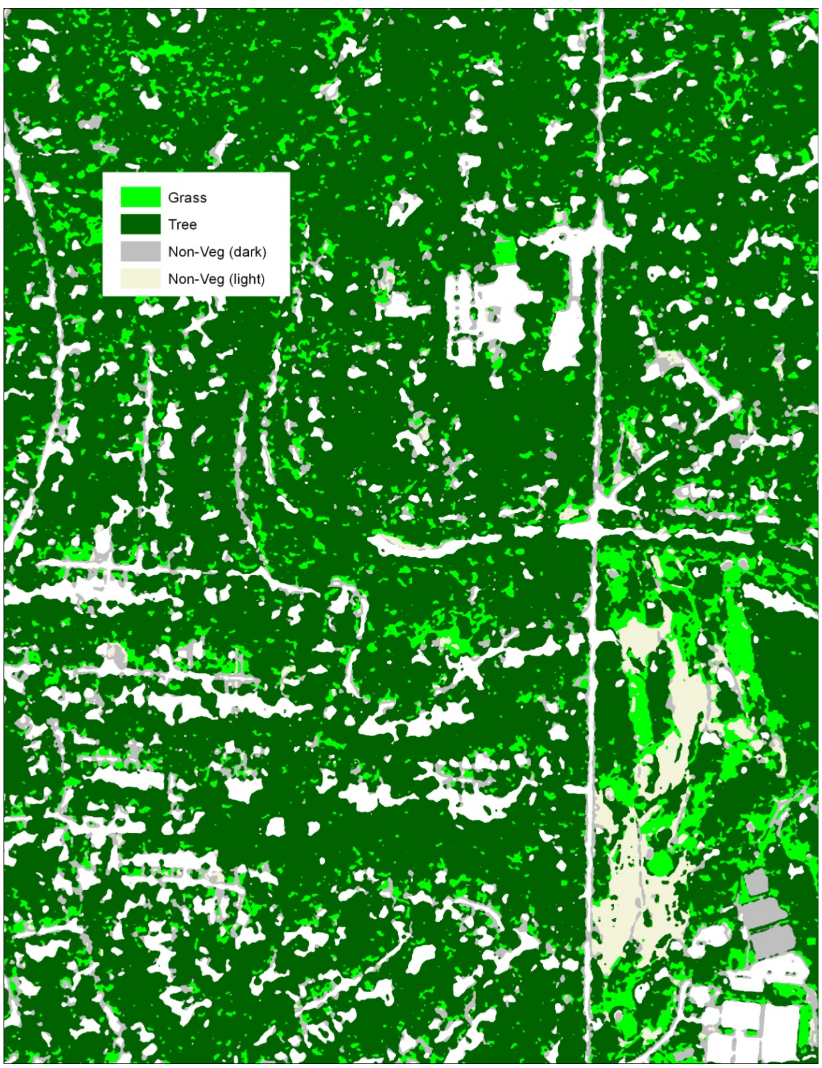
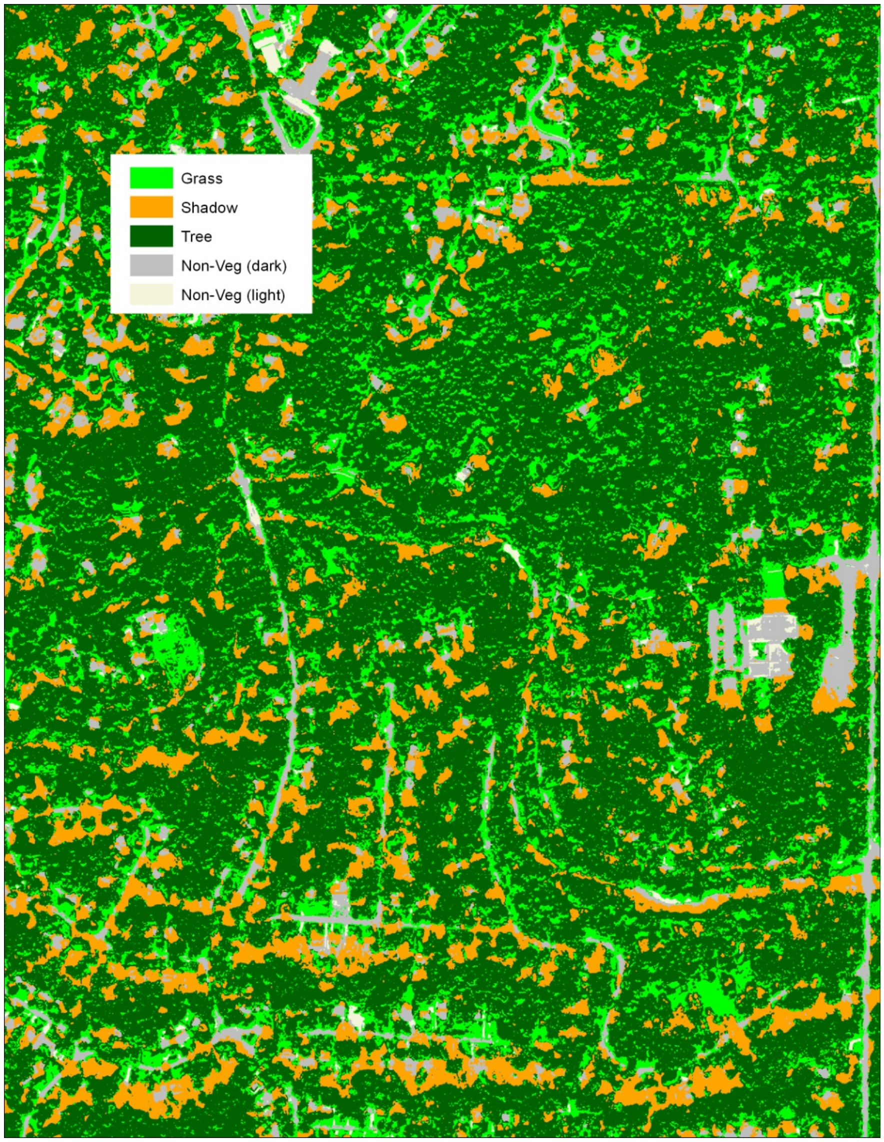


IMAGE 33: FINAL UNSUPERVISED CLASSIFIED IMAGE



Accuracy Assessment

The final step in the land cover classification methodology process is an accuracy assessment for both the supervised and unsupervised classifications. The accuracy assessment process outputs an error matrix, which is a recommended reporting convention, according to Congalton (1991). A good rule of thumb is to collect 50 sample points per land use class. If the area is very large (over 1 million acres) or has a large number of land use categories, then the user should increase the sample size to 75-100 points per category. Furthermore, the number of points can be adjusted per the importance or by the inherent variability of the cateory. Sometimes it is better to focus on a sampling of the categories that are of more interest while increasing its sample number and reducing the sample number of other classes. Other variations may be appropriate. The idea is to get a sampling that balances the statistical requirements for an adequate error matrix (Congalton, 1991).

Since the City of Atlanta is less than 100,000 acres, let alone 1 million acres, and the most classes used is five (in the unsupervised classification process), which calls for 250 sample points, we use 300 points in the accuracy assessments for both classification process, for the sake of comparability. 300 sample points is more than adequate in meeting the requirements that Congalton (1991) lays out for an error matrix.

The sample points are compared against a reference image provided by Google Earth's historical imagery. Google provides historical imagery from 2006 through 2010, which are all used together to help determine the correct land cover classification for the October 2008 Quickbird satellite imagery. In generating the sample points, we choose not random points rather stratified random points, which selects more samples from the larger land covers. Thus, the most sample points in both of the accuracy assessments are from the tree and grass covers.

The images below illustrate the accuracy assessment process for first the supervised classification and then the unsupervised classification. Images 34 through 37 represent the supervised process, and images 38 through 41 represent the unsupervised process.

IMAGE 34: OVERVIEW OF THE 300 SAMPLE POINTS FOR THE SUPERVISED CLASSIFICATION OUTPUT

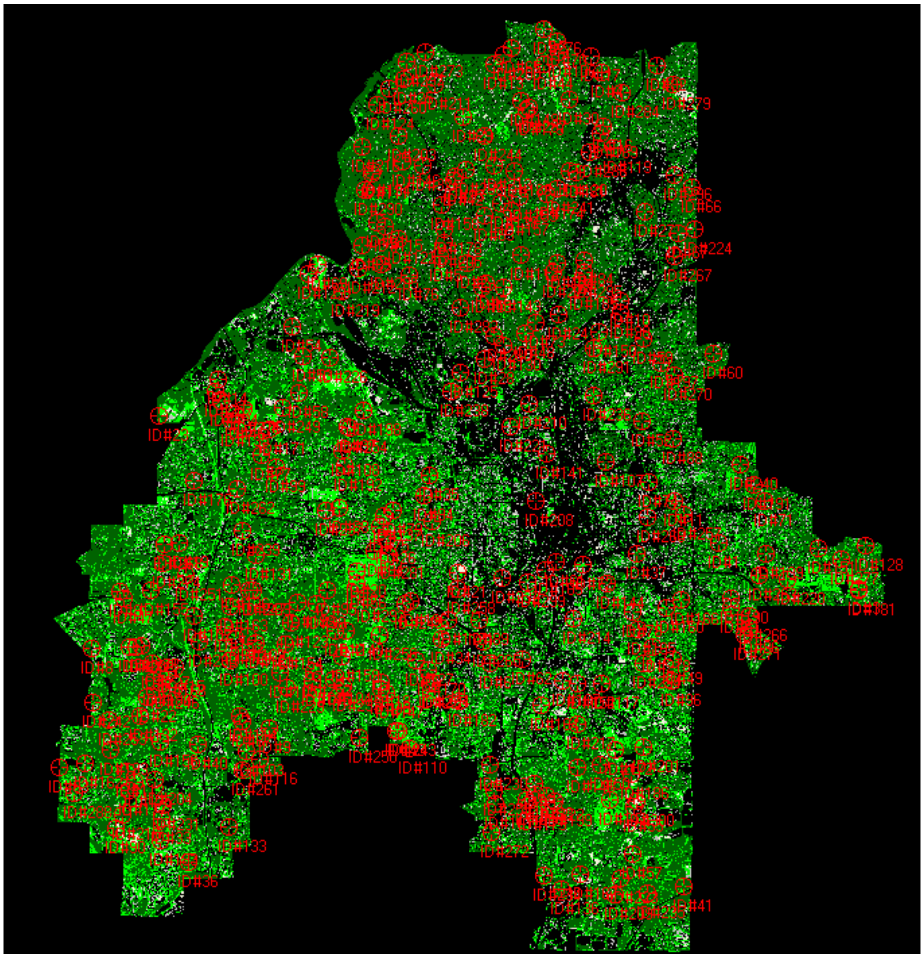


IMAGE 35: ZOOM-IN TO ONE OF THE SAMPLE POINTS FOR THE SUPERVISED CLASSIFICATION OUTPUT

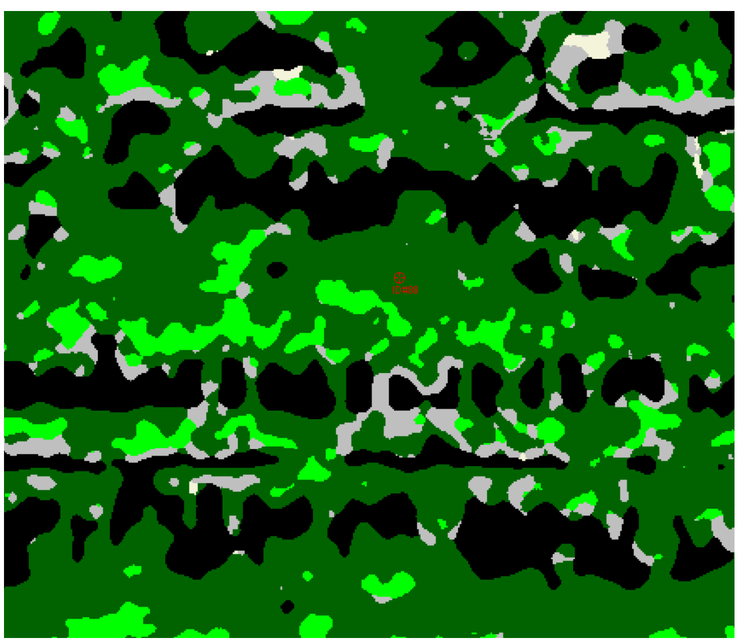


IMAGE 36 & 37: COMPARISON OF THE SUPERVISED LAND COVER FILE TO THE REFERENCE IMAGE (land cover)/ COMPARISON OF THE SUPERVISED LAND COVER FILE TO THE REFERENCE IMAGE (reference image)

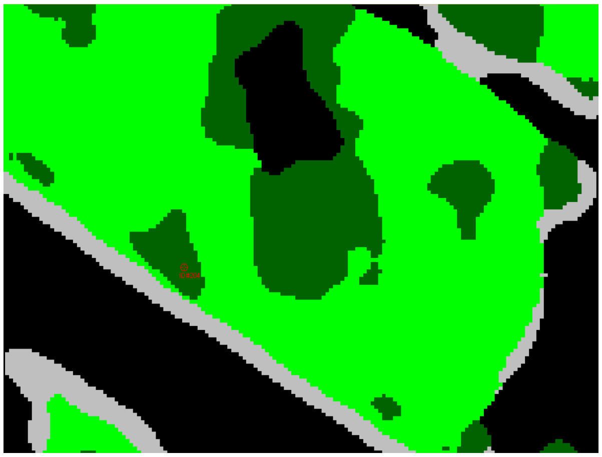


IMAGE 38: OVERVIEW OF THE 300 SAMPLE POINTS FOR THE UNSUPERVISED CLASSIFICATION OUTPUT

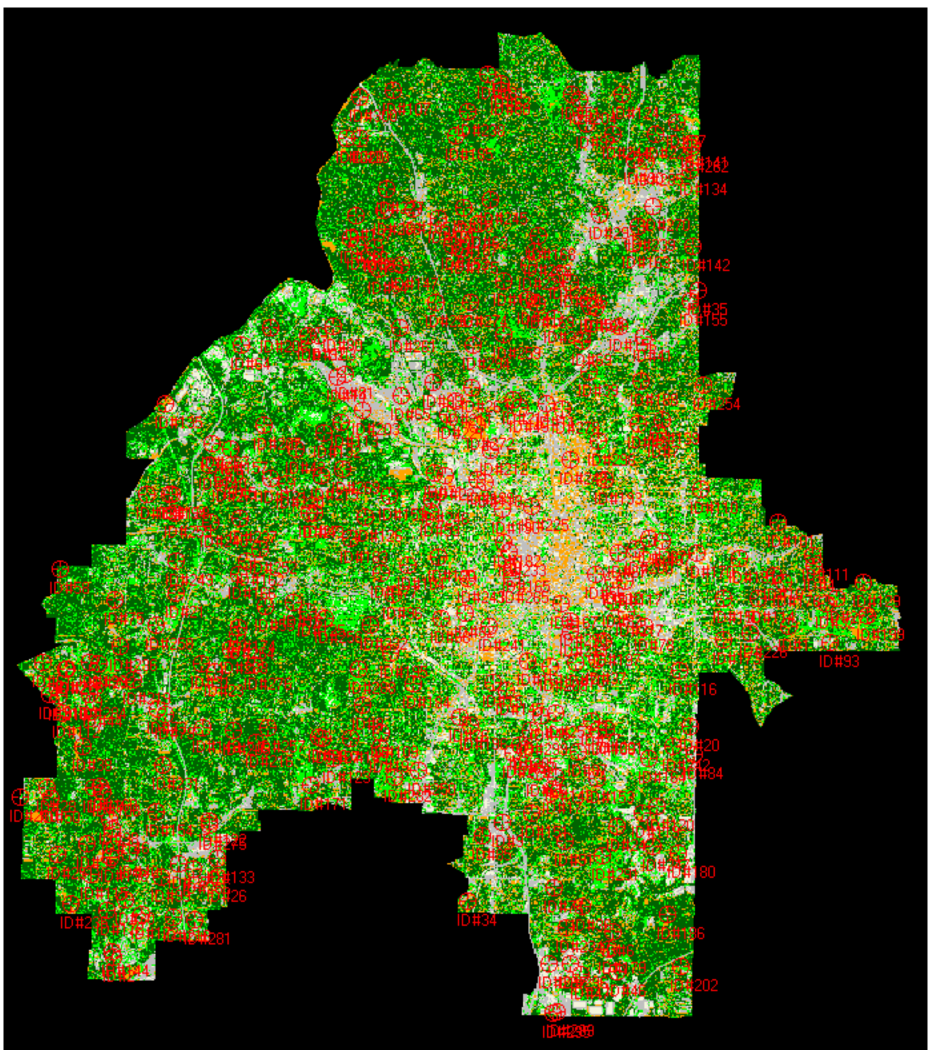
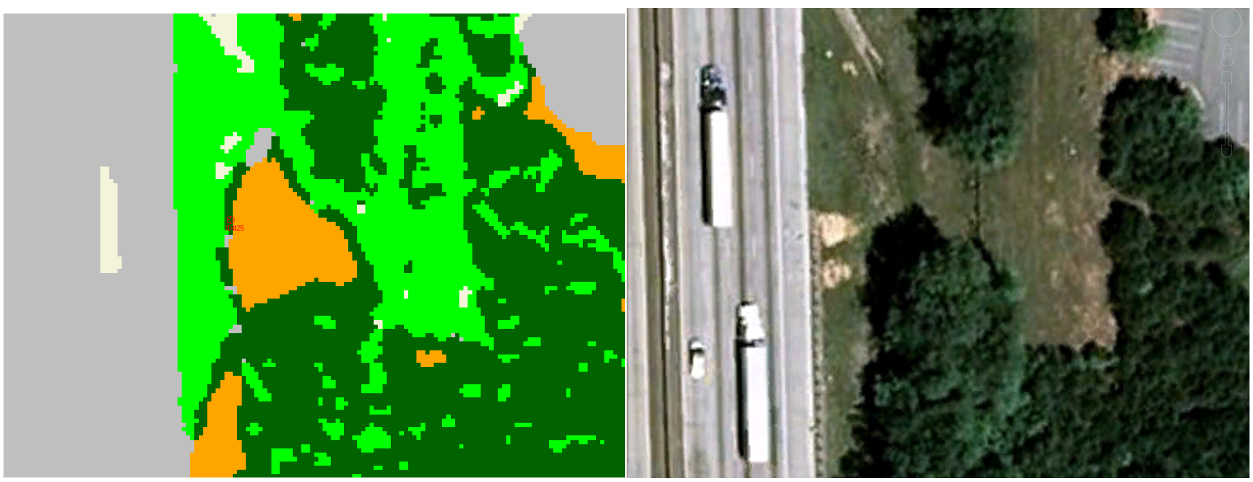


IMAGE 39: ZOOM-IN TO ONE OF THE SAMPLE POINTS FOR THE UNSUPERVISED CLASSIFICATION OUTPUT

IMAGES 40 & 41: COMPARISON OF THE UNSUPERVISED LAND COVER FILE TO THE REFERENCE IMAGE (land cover)/ COMPARISON OF THE UNSUPERVISED LAND COVER FILE TO THE REFERENCE IMAGE (reference image)



RESULTS

User-Defined Classification Process

NDVI: Normalized Difference Vegetation Index

IMAGE 42: MAP OF NDVI RESULTS

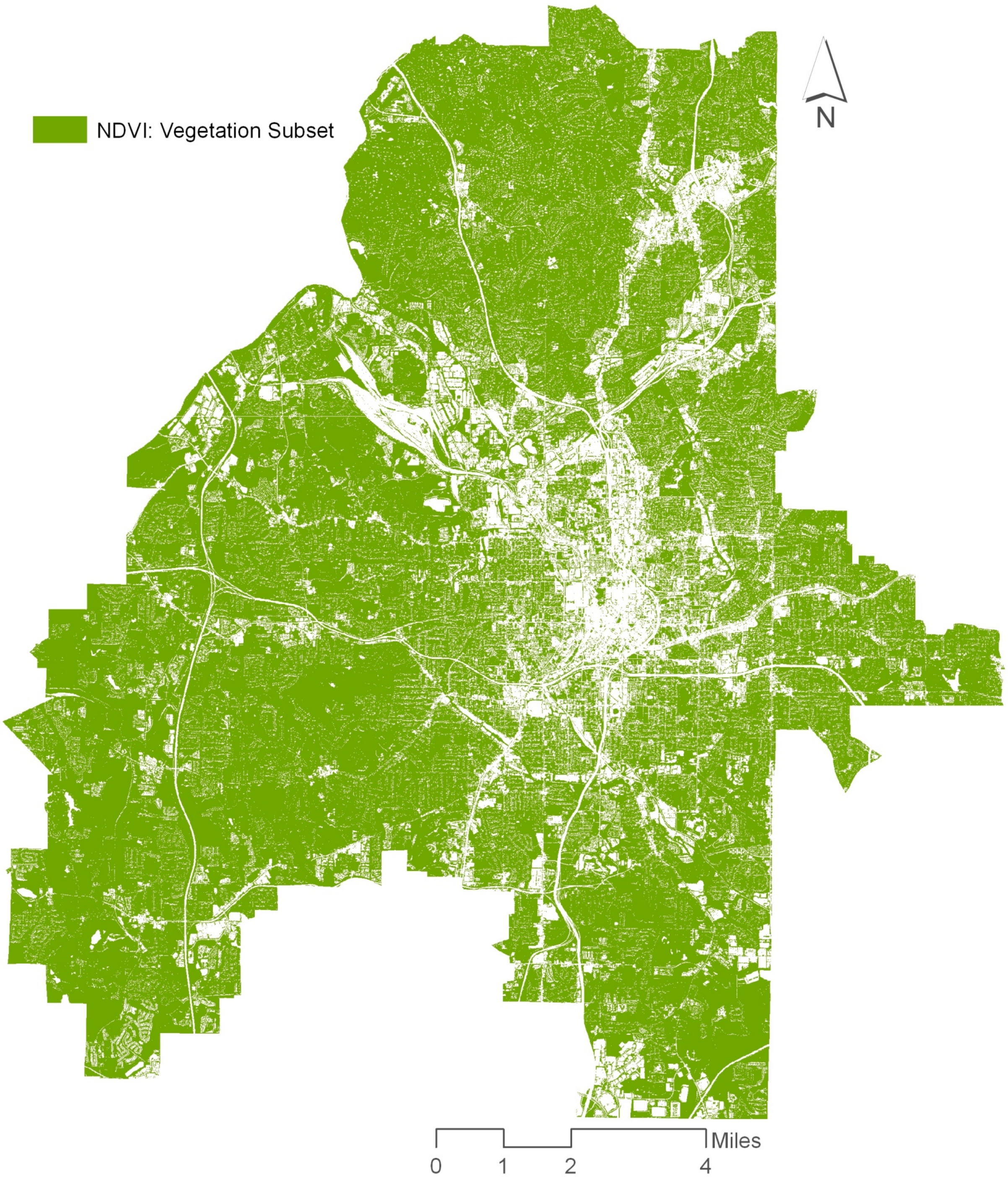


TABLE 2: STATISTICS FOR THE NDVI PROCESS

Land Cover Class	Area (acres)	Total % of City
Vegetaion	65,562.47	76.69%
Non Vegetation	19,931.53	23.31%
City Total	85,494.00	100.00%

The NDVI process determined that 65,562.47 acres of Atlanta's land is vegetation, which is 76.69% of the city's land coverage. This includes any land cover from bare ground to dense trees. In an attempt to capture every single spot of vegetation, this process over estimates vegetation, though. Thus, included in this acreage are some built land covers, including a few roads and small buildings. These errors are minimal, though, and are corrected in the supervised classification processes.

Image 42 is a map of the NDVI process results, which is outlined by table 2.

Supervised Classification

IMAGE 43: MAP OF THE SUPERVISED CLASSIFICATION RESULTS

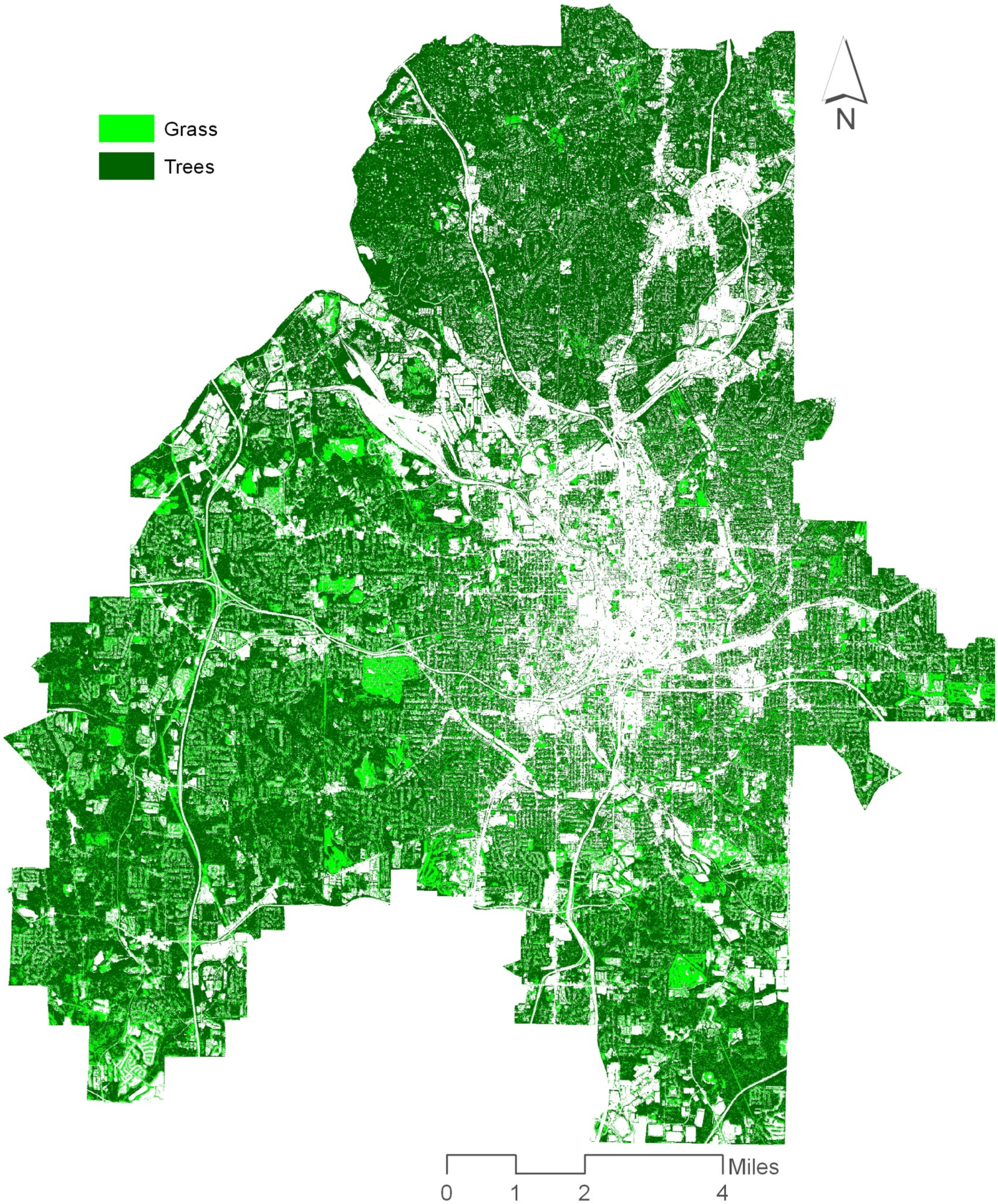


TABLE 3: STATISTICS FOR THE SUPERVISED CLASSIFICATION PROCESS

Land Cover Class	Area (acres)	Total % of City
Grass	13,852.47	16.20%
Trees	44,841.24	52.45%
Non Vegetation	26,800.29	31.35%
Vegetation Total	58,693.71	68.65%
City Total	85,494.00	100.00%

The supervised classification process yielded nearly 60,000 acres of urban vegetation at 68.65% of the city's total coverage and nearly 45,000 of those acres are tree canopy coverage. The urban tree canopy coverage represents 76.40% of the city's vegetation and 52.45% of the city's total acreage. In image 43, the urban tree canopy coverage is represented by the darker green while the rest of urban vegetation is represented by the lighter green color (the grass land cover class).

Image 43 is a map of the supervised classification process results, which is outlined by table 3.

Computer-Defined Classification Process

Unsupervised Classification

IMAGE 44: MAP OF THE UNSUPERVISED CLASSIFICATION RESULTS

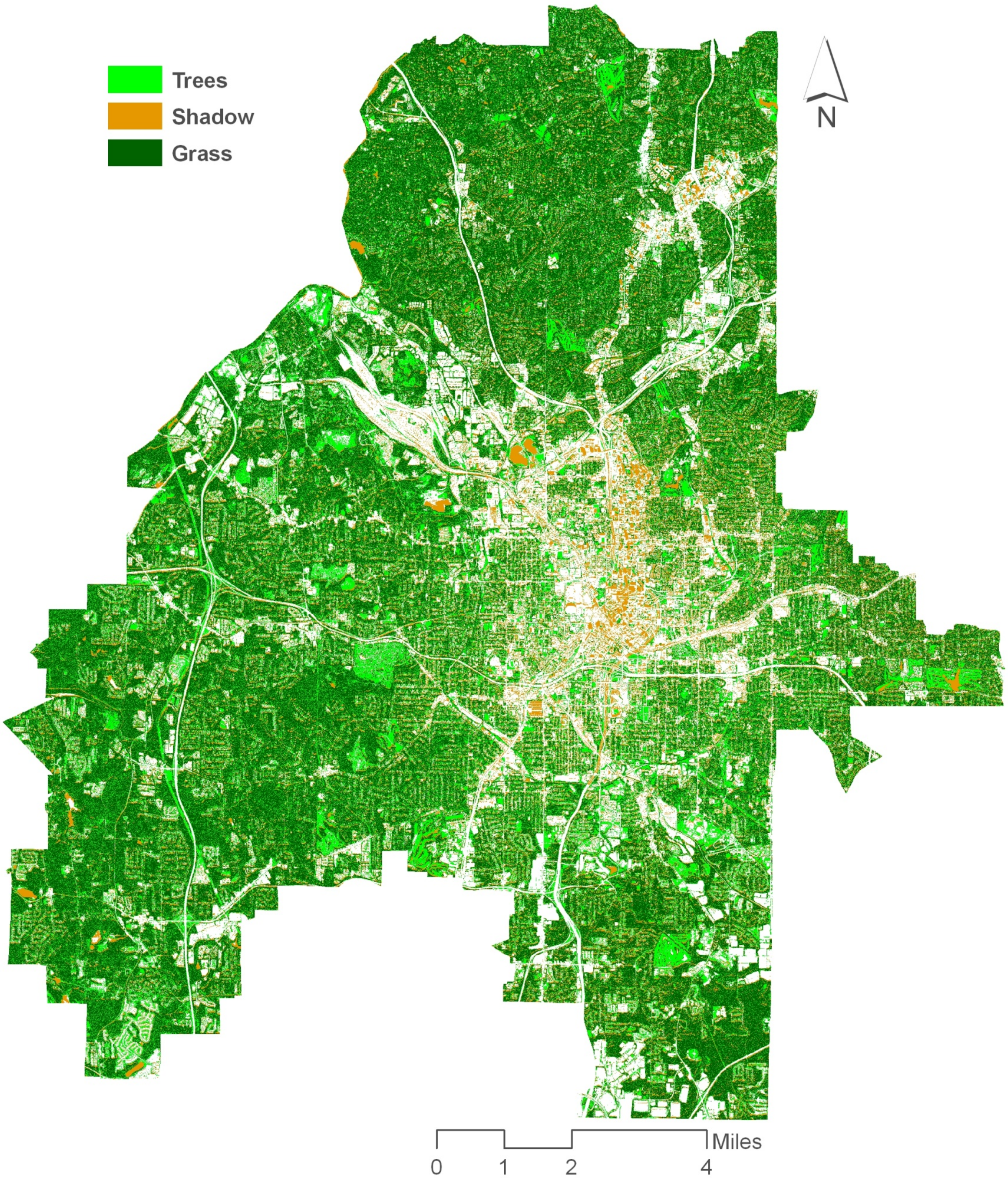


TABLE 4: STATISTICS FOR THE UNSUPERVISED CLASSIFICATION PROCESS

Land Cover Class	Area (acres)	Total % of City
Grass	19,198.08	22.46%
Trees	37,504.00	43.87%
Shadow	11,585.92	13.55%
Non Vegetation	17,206.00	20.13%
Vegetation Total	56,702.08	66.32%
City Total	85,494.00	100.00%

The unsupervised classification process yielded about 57,000 acres of urban vegetation at 66.32% of the city's total coverage and about 37,500 of those acres are tree canopy coverage. The urban tree canopy coverage represents 66.14% of the city's vegetation and 43.87% of the city's total acreage. Within the unsupervised classification's assessment, we must take into account the shadow land cover class, which is eliminated by the user in the supervised classification process. The shadow land cover, about 11,600 acres, represents 13.55% of the Atlanta's total land coverage, which could be taking away from the tree canopy and the total vegetation coverages. The possibility for skewedness is more probable with the presence of the shadow land cover. In image 44, the urban tree canopy coverage is represented by the darker green while the rest of urban vegetation is represented by the lighter green color (the grass land cover class), and the shadow coverage is shown in orange.

Image 44 is a map of the supervised classification process results, which is outlined by table 4.

Comparing the Urban Vegetation and Urban Tree Canopy Coverage Results

TABLE 5: URBAN VEGETAION AND TREE CANOPY COVERAGE RESTULS COMPARISON

URBAN VEG	NDVI		Supervised		Unsupervised	
LAND COVER	Area (acres)	% City Total	Area (acres)	% City Total	Area (acres)	% City Total
Vegetation	65,562.47	76.69%	58,693.71	68.65%	56,702.08	66.32%
Tree Canopy	-	-	44,841.24	52.45%	37,504.00	43.87%

For urban total vegetation, the NDVI process claims the highest acreage. As previously stated, this amount is slightly skewed because of the overcompensation of pixel gathering in the original process in order to obtain every single piece of possible vegetation. Thus, the supervised classification displays a more accurate result of total vegetation due to the further elimination of non-vegetation land cover classes. The supervised classification vegetation calculation represents 89.52% of the vegetation class that the NDVI process reported; that is a difference of less than 7,000 acres. The supervised classification's urban vegetation result is 3.39%, or nearly 2,000 acres, greater than that of the unsupervised classification. Again, this difference could be due to the shadow land cover class that is present in the unsupervised classification results. However, this percent change is relatively minimal.

Likewise, the supervised classification process yielded a higher area of tree canopy coverage than the unsupervised classification: 16.36% more, or over 7,000 acres. The NDVI process is not applicable in the tree canopy coverage measurement because it illustrates urban vegetation as one aggregated land cover rather than separated classes. The urban vegetation and tree canopy coverage totals (area in acres and percentage of the city's total area) are displayed in table 5.

Accuracy Assessment Results

There are three types of accuracy given by an accuracy assessment: overall classification, producers, and users. The overall classification accuracy reports the ratio of number of correctly identified sample points to the total number of sample points. Producer and user accuracies refer to the idea of reference-based accuracy and map-based accuracy, respectively. According to the Center for Biodiversity and Conservation, producer's accuracy is the ratio of sample points correctly classified in one category compared to the total number of sample points of the same class that are identified in the reference image. On the other hand, user's accuracy is the ratio of misclassed sample points in a certain category compared to the total number of sample points within that same class that the classification process originally delineated.

Supervised Classification

The supervised classification accuracy assessment results yielded an overall classification accuracy of 78.67%, or 236 out of 300 correctly identified sample points. The most important land cover class to notice, though, is the tree class because that is the land cover we focused on the most for the City of Atlanta's urban tree cover canopy coverage. The producer's accuracy, or the accuracy derived from the reference image, for tree canopy coverage is 84.04% and is 91.26% for user's accuracy, or the accuracy derived from the classified map image. Of all the land cover categories, the tree canopy has the highest accuracy for both producer's and user's. Table 6 shows per class the total number of sample points correctly identified, producer's accuracy, user's accuracy, and the overall classification accuracy for the supervised classification accuracy assessment.

TABLE 6: ERROR MATRIX FOR THE SUPERVISED CLASSIFICATION ACCURACY ASSESSMENT

CLASS	# Correct	Producer's Accuracy	User's Accuracy
Grass	33	60.00%	51.56%
Tree	188	84.04%	91.26%
Non Veg (dark)	11	61.11%	44.00%
Non Veg (light)	4	40.00%	80.00%
Overall Classification Accuracy		**78.67%**	

Unsupervised Classification

The unsupervised classification accuracy assessment results yielded an overall classification accuracy of 66.00%, or 198 out of 300 correctly identified sample points. Again looking at the most important land cover class, tree canopy, the producer's accuracy (reference-based) is 70.63% and the user's accuracy (classified map-based) is 78.91%. Table 7 shows per class the total number of sample points correctly identified, producer's accuracy, user's accuracy, and the overall classification accuracy for the unsupervised classification accuracy assessment.

TABLE 7: ERROR MATRIX FOR THE UNSUPERVISED CLASSIFICATION ACCURACY ASSESSMENT

CLASS	# Correct	Producer's Accuracy	User's Accuracy
Grass	34	69.39%	51.52%
Shadow	11	42.31%	27.50%
Tree	101	70.63%	78.91%
Non Veg (dark)	38	74.51%	80.85%
Non Veg (light)	14	45.16%	73.68%
Overall Classification Accuracy		**66.00%**	

Classification Comparison

The overall accuracy of the supervised classification process is 12.67% higher than the overall accuracy of the unsupervised classification. Similarly, the supervised classification's results for producer's and user's accuracies are higher than their counterparts in the unsupervised classification. The supervised classification's producer's accuracy is 13.41% higher, and its user's accuracy is 12.35% higher.

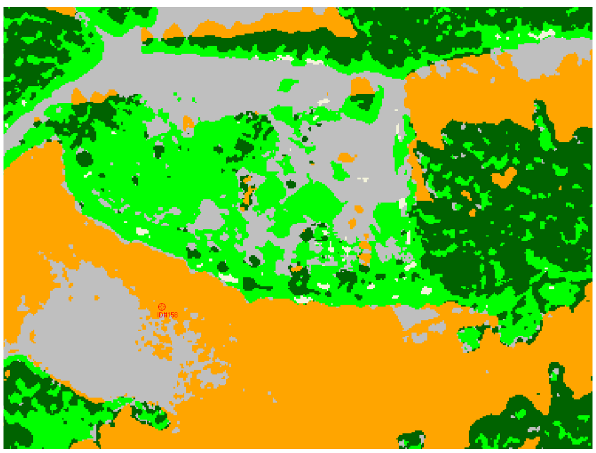
Based on all three of the accuracy percentages addressed in this analysis, the supervised classification process better represents the overall accuracy of the true land cover with particular notice to tree canopy coverage.

Thus, we acknowledge and accept that the more accurate amounts of urban vegetation and urban tree canopy coverage for inside Atlanta's city limits are 58,694 acres (68.65% of the city's total area) and 44,841 acres (52.45% of the city's total area), respectively, which are derived from a supervised classification process taken from a subset of an NDVI function.

A major source of error in the unsupervised classification is apparent because of the presence of a shadow land cover class. The true land cover of this area, 11,586 acres (13.55% of the city's total area), is not actually shadow; rather, this area one of the other land covers. The computer cannot differentiate between the shadow and the true land cover. In a supervised classification, the user, or human, can define the shadowed pixels appropriately, which is another argument in support of accepting the land cover values for the supervised method.

Furthermore, this unsupervised methodology does not account for water as a land cover because of the focus on vegetation and tree canopy. However, Atlanta does contain some areas of surface water. Much of the water land cover is included in the shadow coverage, which could be a remedy. However, as seen in images 45 and 46, the entirety of the water body is not classified as shadow (orange); in this case, it is partially classified as dark urban. Misclassifications like this happen throughout the image. In general, the shadow classification determined by the computer's pixel signature delineation has proven to be problematic. It shows up in many places that are not shadowed and conversely does not cover other areas that are obviously shadowed.

IMAGE 45 & 46: UNSUPERVISED CLASSIFICATION: MISCLASSED SHADOW/WATER LAND COVER/GOOGLE EARTH REFERENCE IMAGE: MISCLASSES SHADOW/WATER LAND COVER



URBAN TREE CANOPY COVERAGE FOR THE GEOGRAPHIES OF CITY OF ATLANTA

The whole idea behind gathering that statistics for urban vegetation and tree canopy cover is to aid in decision-making for the maintenance and growth of the natural environment, which has many beneficial implications. As previously outlined, four main categories surface in a discussion regarding the benefits of urban vegetation and tree canopy coverage: environmental, hydrology, urban design, and socioeconomic. Each of these themes are made up of numerous sub categories, such as reducing the effect of urban heat islands and lowering the temperatures in cities; the list goes on and on within each category. In this section, however, I focus on the analysis of tree canopy coverage for one type of geography within the four main categories. For environmental I focus on land uses. For hydrology, the focus is on hydrologic unit code delineated areas. The focus for urban design is public safety. And, the focus for socioeconomic is analysis of block level data from the U.S. Census Bureau. In addition to the initial four categories identified as having a relationship with urban vegetation, I discuss a fifth category, which is that of political. It is important for a political discussion of urban vegetation and tree canopy coverage. Needed growth and change of urban vegetation is only possible if these discussion take place.

Because the City of Atlanta asked for specifics on the urban tree canopy coverage, rather than urban vegetation as a whole, the focus in this section only refers to the former land cover class but not the latter.

First, though, I conduct a grid analysis of Atlanta's tree canopy coverage to illustrate exactly where tree canopy is located now. In order to show where urban tree canopy coverage is currently centralized for the City of Atlanta, a 500 by 500 grid is joined to a raster subset of only the tree canopy class. Image 47 shows the tree canopy coverage subset, image 48 shows the 500 by 500 grid, and image 49 is the outcome of the tree canopy coverage and the grid, which is a percentage of tree canopy coverage for thousands of cells that represent all of the areas of the city. The most striking areas of minimal tree canopy coverage are in the very central portion of the city, which contains the denser neighborhoods and is where the crossroads of numerous major interstates and streets meet.

IMAGE 47 & 48: SUBSET OF THE CITY OF ATLANTA'S TREE CANOPY COVERAGE /ZONAL STATISTICS: 500X500 GRID

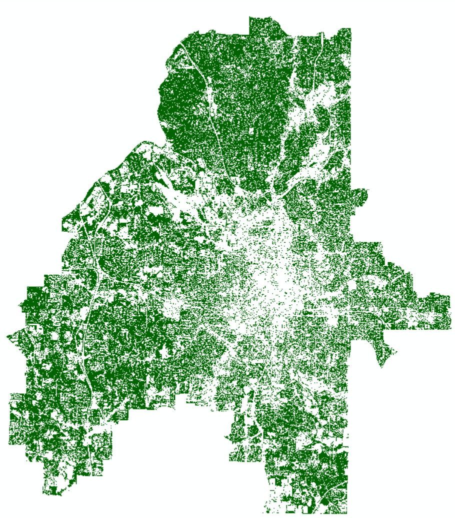
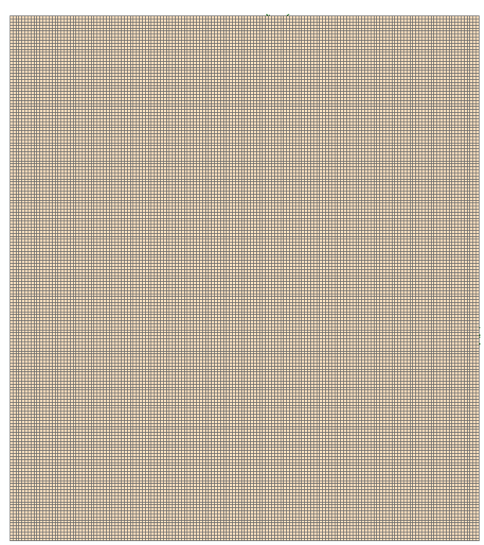
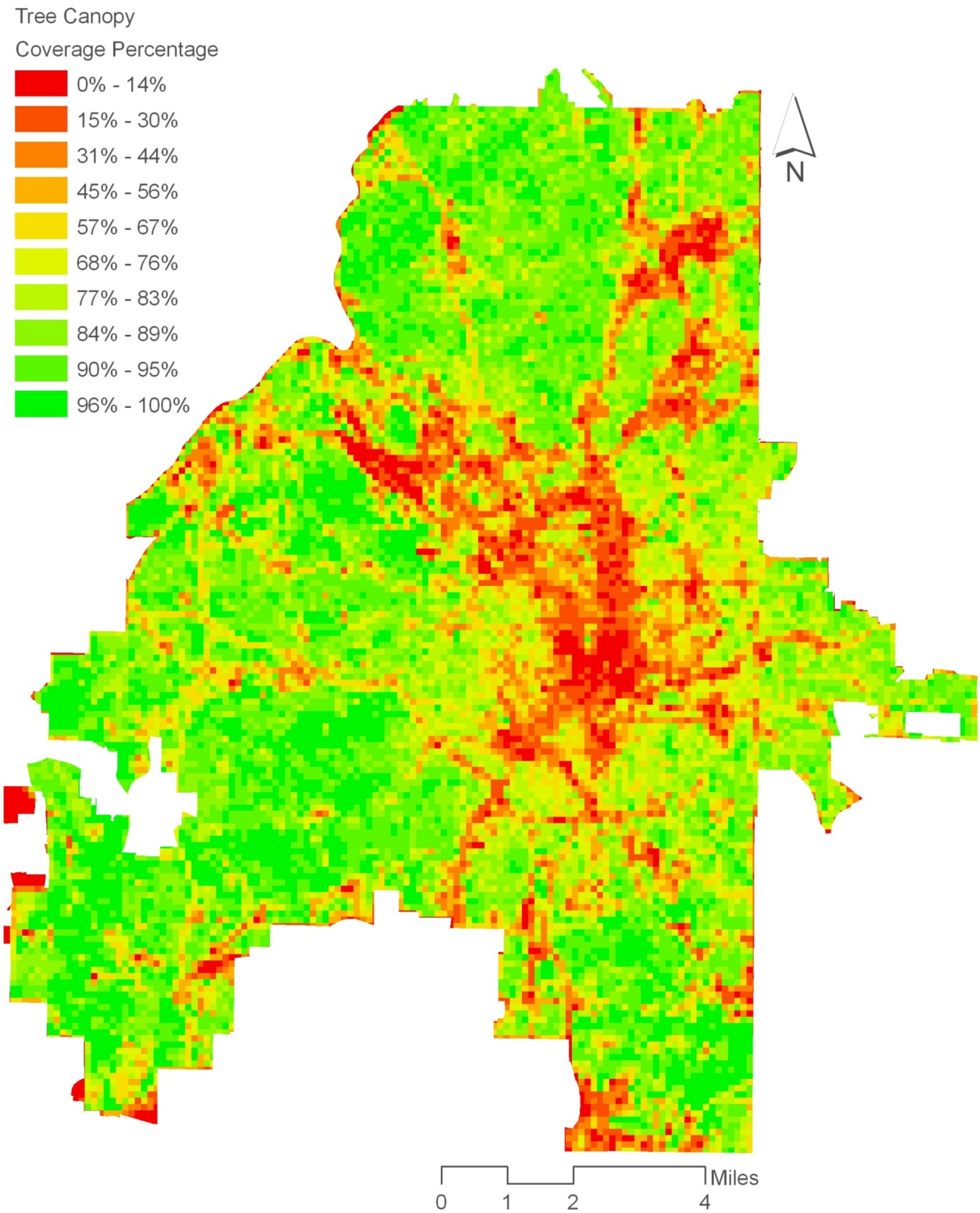



IMAGE 49: ZONAL STATISTICS: TREE CANOPY COVERAGE PERCENT PER CELL



Environmental Benefits

Land use monitoring is important in the environmental implications of urban tree canopy coverage. According to Veldkamp & Verburg (2004), land uses' change in particular can have serious impacts on the environmental health of a city. In fact, they propose a land use/cover change (LUCC) model to interpret the cause and effects of such change on urban natural environments as well as the impact on the other categories discussed below. Not only are particular land uses more detrimental to the natural environment, like quarries and industrial, but the change from one land use to another can be a stressor on nature if not handled properly.

Image 50 shows the beak down of 22 land uses delineated from the Atlanta Regional Commission's LandPro 2010 data. This map is somewhat difficult to interpret because all of the land uses are intertwined with one another. It is helpful, though, in interpolating tree canopy coverage percentages for each specific cover. Specifically, I determined the land uses with the most percentage of tree coverage and its counterpart with the least tree coverage. Note: excluded from the least tree coverages are the water body coverages (lakes, rivers, and reservoirs) and land uses that are less than 5 square miles in area. As seen in image 51, the land use with the highest percentage of tree canopy coverage is high density residential, which is primarily centralized to central and southeastern area of the city. The land cover with the least tree canopy coverage percentage is commercial. As seen in image 52, the commercial land use is scattered broadly across the city, but it does have a few trends, which are following relatively closely to major interstates and corridors, including the corridors running from Downtown, through and past Midtown, and up to Buckhead.

The higher density residential land cover with the highest percentage of urban tree canopy cover consists of over 12,000 acres, or 14% of the entire city, which, fortunately for the natural environment, is larger than the almost 8,500 acres of commercial land cover, or almost 10% of the entire city.

IMAGE 50: URBAN TREE CANOPY COVERAGE PERCENTAGE PER LAND USE TYPE

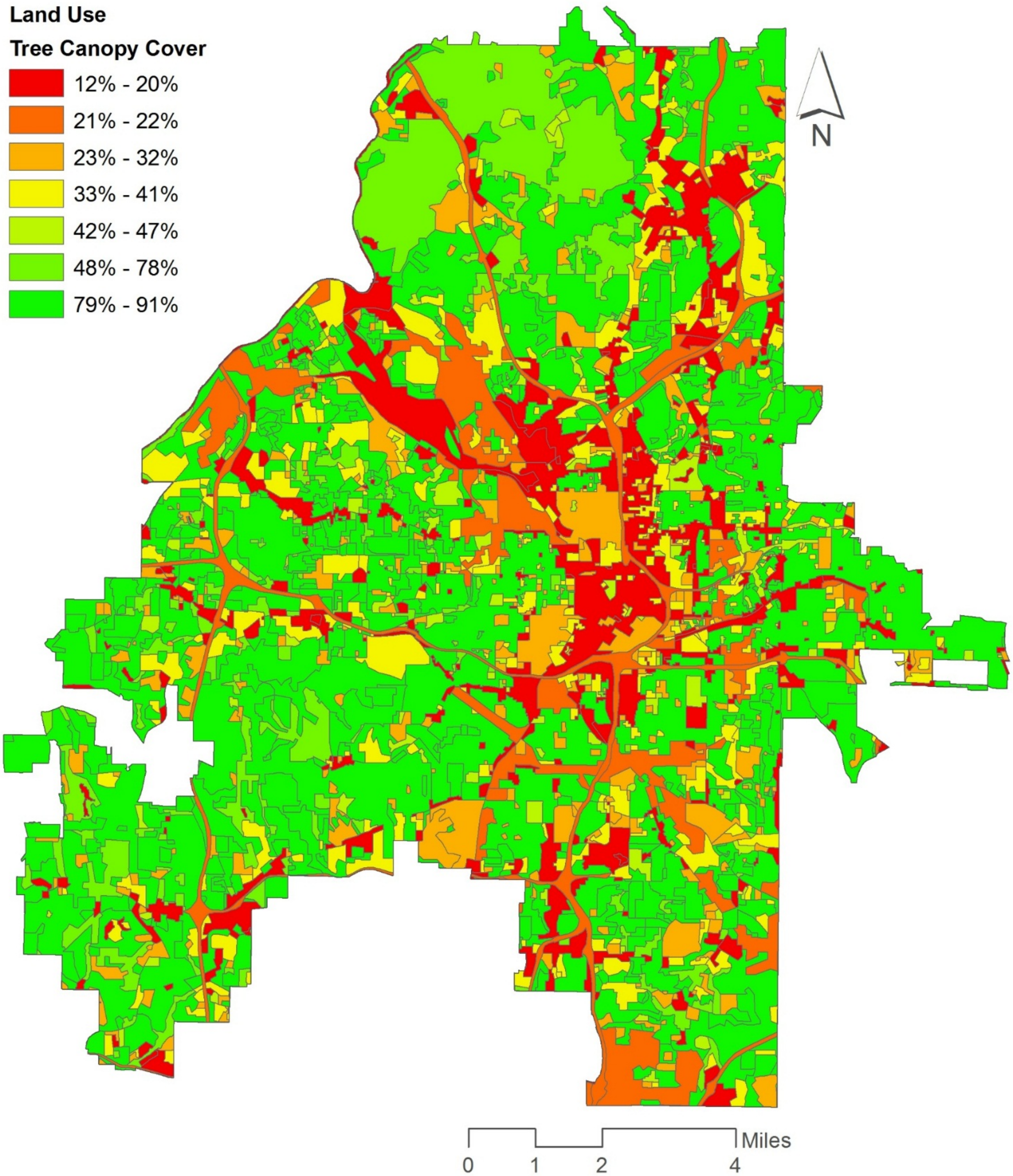


IMAGE 51: LAND USE WITH THE HIGHEST PERCENTAGE OF TREE CANOPY COVER: RESIDENTIAL (high)

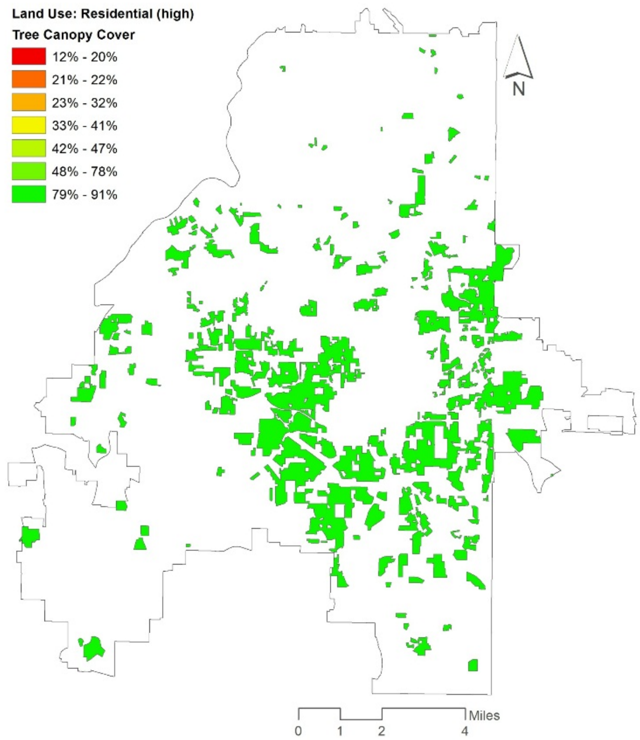


IMAGE 52: LAND USE WITH THE LOWEST PERCENTAGE OF TREE CANOPY COVER: COMMERCIAL (excluding bodies of water and areas of lesser significant size/under 5 square miles)

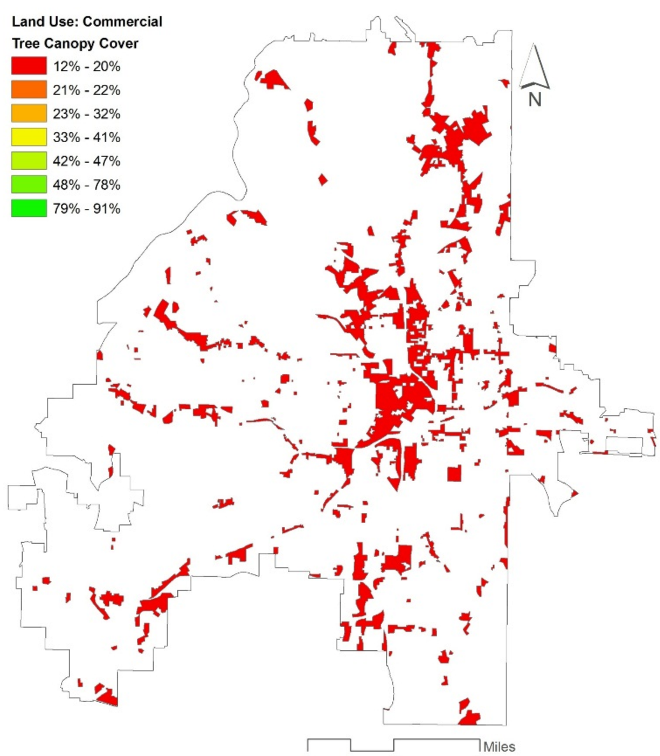


Table 8 delineates the total area, tree canopy area, and tree canopy coverage percent for all 22 land uses delineated from the Atlanta Regional Commission. The green highlights the residential high density land use, the darker red highlights the commercial land use, and the lighter red identifies the land uses with lower percentages of tree canopy coverage but are not included in the discussion for previously discussed reasons.

TABLE 8: LAND USE STATISTICS RESULTS

LAND USE TYPE

CATEOGRY	TOTAL AREA (acres)	TREE CANOPY AREA (acres)	TREE CANOPY COVERAGE %
Agriculture	99.08	41.51	41.90%
Cemeteries	826.09	267.44	32.37%
Commercial	8,466.02	1,687.41	19.93%
Forest	9,611.17	7,877.60	81.96%
Golf Courses	1,108.80	357.98	32.29%
Industrial/Commercial	4,385.22	913.24	20.83%
Inudustrial	676.03	138.78	20.53%
Institutional Intensive	4,263.04	1,222.69	28.68%
Limited Access	2,384.25	513.90	21.55%
Parks	1,614.78	762.76	47.24%
Quarries	109.87	50.49	45.96%
Residential High	12,344.60	11,251.99	91.15%
Residential Low	8,017.84	6,281.50	78.34%
Residential Medium	20,549.30	17,522.71	85.27%
Residential Mobile	31.74	18.29	57.63%
Residential Multi-Family	5,974.03	1,975.78	33.07%
Resevoirs	171.11	21.88	12.79%
Rivers	120.59	14.54	12.06%
TCU (infrastructure)	2,000.50	296.27	14.81%
Transitional	1,556.69	433.07	27.82%
Urban Other	1,082.27	438.43	40.51%
Wetlands	323.57	225.37	69.65%

Hydrology

Hydrology is obviously a part of the natural environment, the previously mentioned category. However, because of the massive and intricate water systems that cities rely on, it deserves its own category of observation. Furthermore, to reiterate CGIS & CQGRD's study proposal (2012), Atlanta sits on top of numerous watersheds that sprout even more streams. In reference to hydrological implications of tree canopy coverage, I looked at the city's tree canopy coverage percentage for each of the 12 digit hydrologic unit code (HUC 12) watersheds that are both fully or partially within Atlanta's limits. The tree canopy coverage percentage for the HUC 12 watersheds remains high throughout the center of the city, from top to bottom. The largest area with the lowest percentage of tree canopy coverage is to the southeast area of the city. Image 53 illustrates the HUC 12 watersheds and percent of tree canopy coverage for each along with table 9.

As previously stated, there are many benefits that tree canopies have on hydrologic systems. One is particular is the reduction of water temperature, which aids in the reduction of evaporation, which helps maintain the water drinking supply. By visualizing the HUC 12 watersheds lacking tree canopy coverage, appropriate policies can be implemented to mitigate any drinking water loss.

IMAGE 53: URBAN TREE CANOPY COVERAGE PERCENTAGE PER 12 HYDROLOGIC UNIT CODE WATERSHED

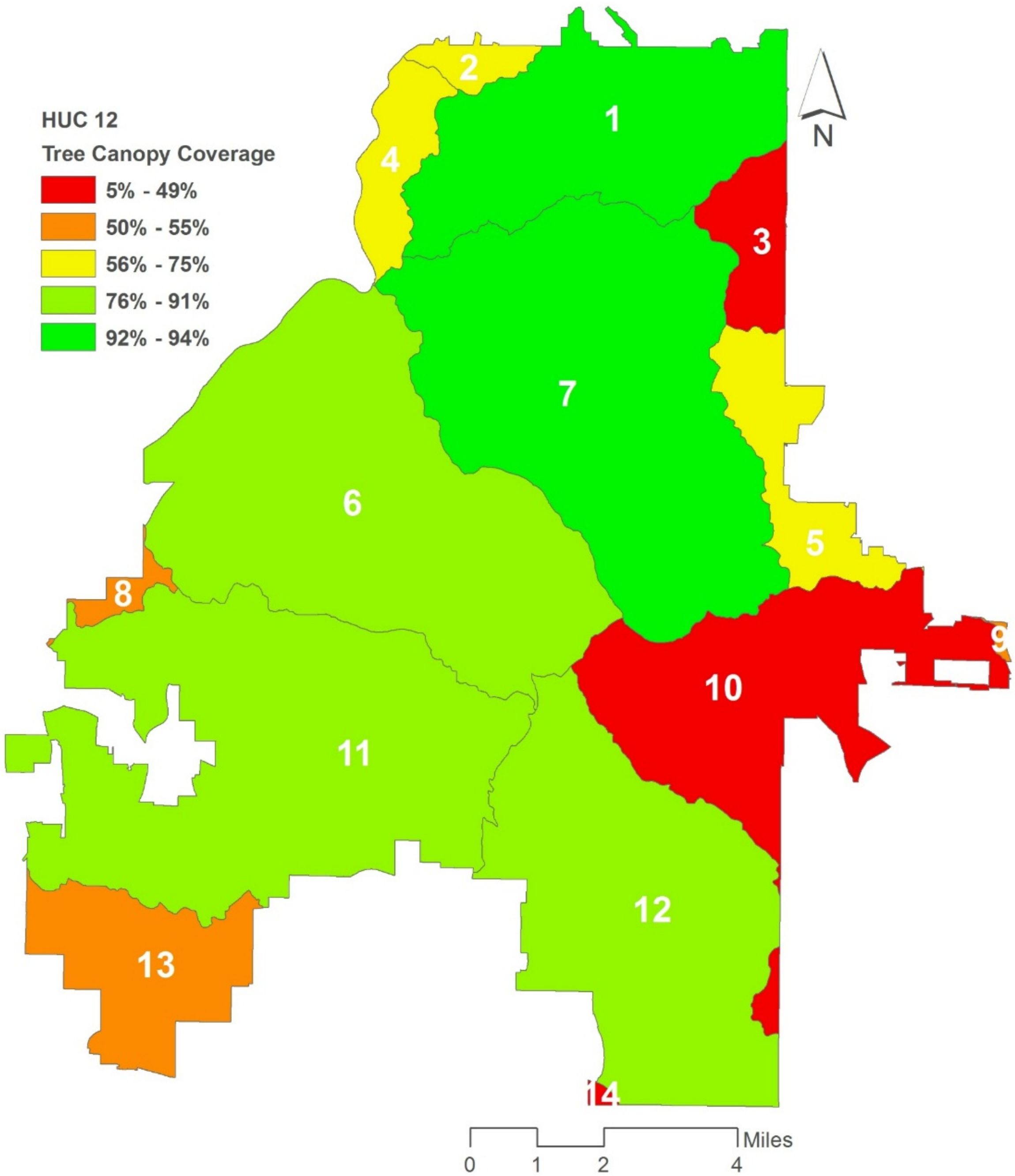


TABLE 9: HUC 12 WATERSHED STATISTICS RESULTS

HYDROLOGIC UNIT CODE

HUC 12	TOTAL AREA (acres)	TREE CANOPY AREA (acres)	TREE CANOPY COVERAGE %
30701030101	11,640.15	10,596.06	91.03%
30701030102	8,073.28	3,412.30	42.27%
30701030103	62.33	32.70	52.46%
31300011105	618.01	460.79	74.56%
31300011106	1,640.00	1,223.65	74.61%
31300011201	1,618.33	792.67	48.98%
31300011202	2,609.09	1,476.35	56.59%
31300011203	8,011.35	7,354.04	91.80%
31300011204	15,430.94	14,434.98	93.55%
31300020101	15,434.07	13,788.07	89.34%
31300020103	15,925.13	14,189.93	89.10%
31300020104	426.69	236.38	55.40%
31300020302	3,921.24	1,931.56	49.26%
31300050101	301.25	14.16	4.70%

Urban Design

Of the many considerations of sub categories that fall under the urban design implications of urban tree canopy coverage, I focus on the public safety idea. One idea of urban design is that an aesthetically pleasing area thwarts crime. For instance, a University of Pennsylvania study concludes that cleaning up, or regreening, urban vacant lots reduces crime. The researchers took a random sample of variously vegetated vacant lots in Philadelphia, which supported their hypothesis. Thus, a knowledge of tree canopy coverage per police beat can act as a tool for crime reduction and the increase of public safety (Avril, 2011).

Image 54 illustrates the percent of tree canopy coverage per police beat in Atlanta. Table 10 only includes the two police beats with the highest and lowest percentage of tree canopy coverage, along with total areas, tree canopy area, and tree canopy coverage percentage. Note: beat 511, the lowest, has the lowest canopy coverage except for the one reported beat that has a zero percentage tree canopy.

IMAGE 54: URBAN TREE CANOPY COVERAGE PERCENTAGE PER POLICE BREAK (public safety)

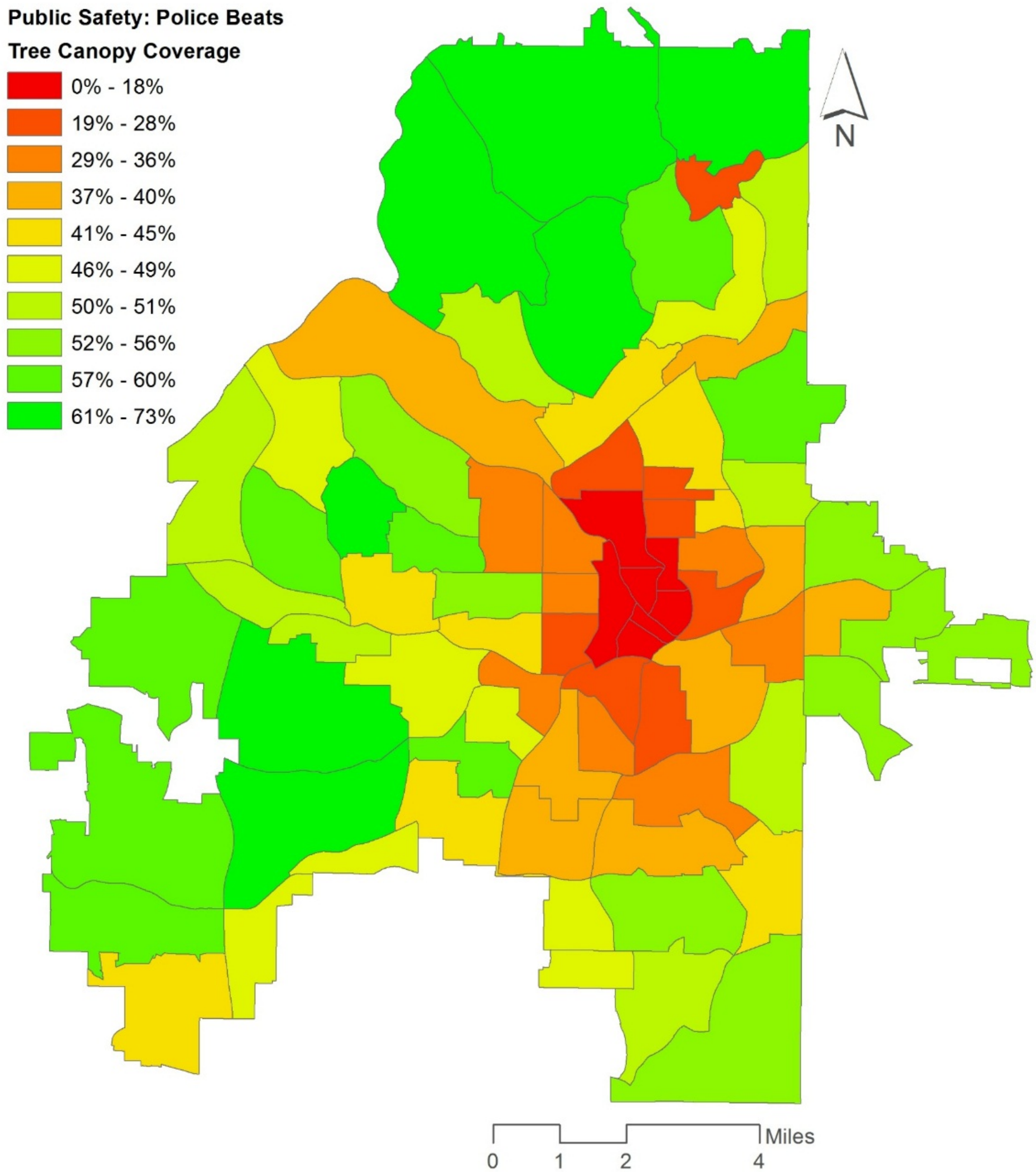


TABLE 10: PUBLIC SAFETY: POLICE BEAT STATISTICS RESULTS (best and worst tree canopy coverage percentage)

	POLICE BEAT	TOTAL AREA (acres)	TREE CANOPY AREA (acres)	TREE CANOPY COVERAGE %
PUBLIC SAFETY	202	4,557.95	3,341.61	73.31%
	511*	95.39	4.39	4.61%

*Above zero acres

Socioeconomic

Socioeconomic factors are represented via numerous types of geographies, however, a reliable source for data is always the U.S. Census Bureau. Along with the decennial census, the Bureau reports at least some statistics every single year at comparable geographies. This makes the data very usable and able to detect changes easily. For this study's purpose, I use the Census delineated block level geography.

The Census has demographic data ranging from household size to single mothers per block group. Harnessing this nation-wide data is a powerful tool for decision-making and bettering the social environments of the less fortunate. For instance, socioeconomic status is hypothesized to be positively related to amounts of urban vegetation (Kinzing, et al., 2005). By identifying the Census blocks that have lower amounts of urban vegetation and tree canopy coverage, planners and decision-makers can implement appropriately placed policy to help the socioeconomically vulnerable populations.

Like the land use data discussed in the environmental section, the Census blocks are hard to distinguish between; this is obvious in image 55 that shows all of the percentage of tree canopy coverage for all bocks. But also like the land use data, more specific trends can be interpolated from this image. Image 56 shows the blocks with less than 25 percent tree canopy coverage. With a few blocks scattered throughout the city, the vast majority of these blocks are centralized in the Downtown area and up through Midtown. Image 57 shows the converse of Census blocks with more than 75 percent tree canopy coverage. The majority of these blocks are located in the northern portion of the city. The average lowest tree canopy coverage quantile is about 12 percent and consists of nearly 14,000 acres or 16 percent of the total city area. The average highest tree canopy coverage quantile is right at 80% and consists of about 11,600 acres or 13.5 percent of the total city area. If we maintain that a denser tree canopy coverage is desirable, then Atlanta's inner-city blocks need help to increase said canopy in order to receive the positive externalities associated with urban trees.

Table 11 reports the lowest and highest quantile of the percentage of tree canopy coverage as a new average of each quantile as a whole, and includes total areas, tree canopy area, and tree canopy coverage percentage.

IMAGE 55: URBAN TREE CANOPY COVERAGE PERCENTAGE PER CENSUS BLOCK

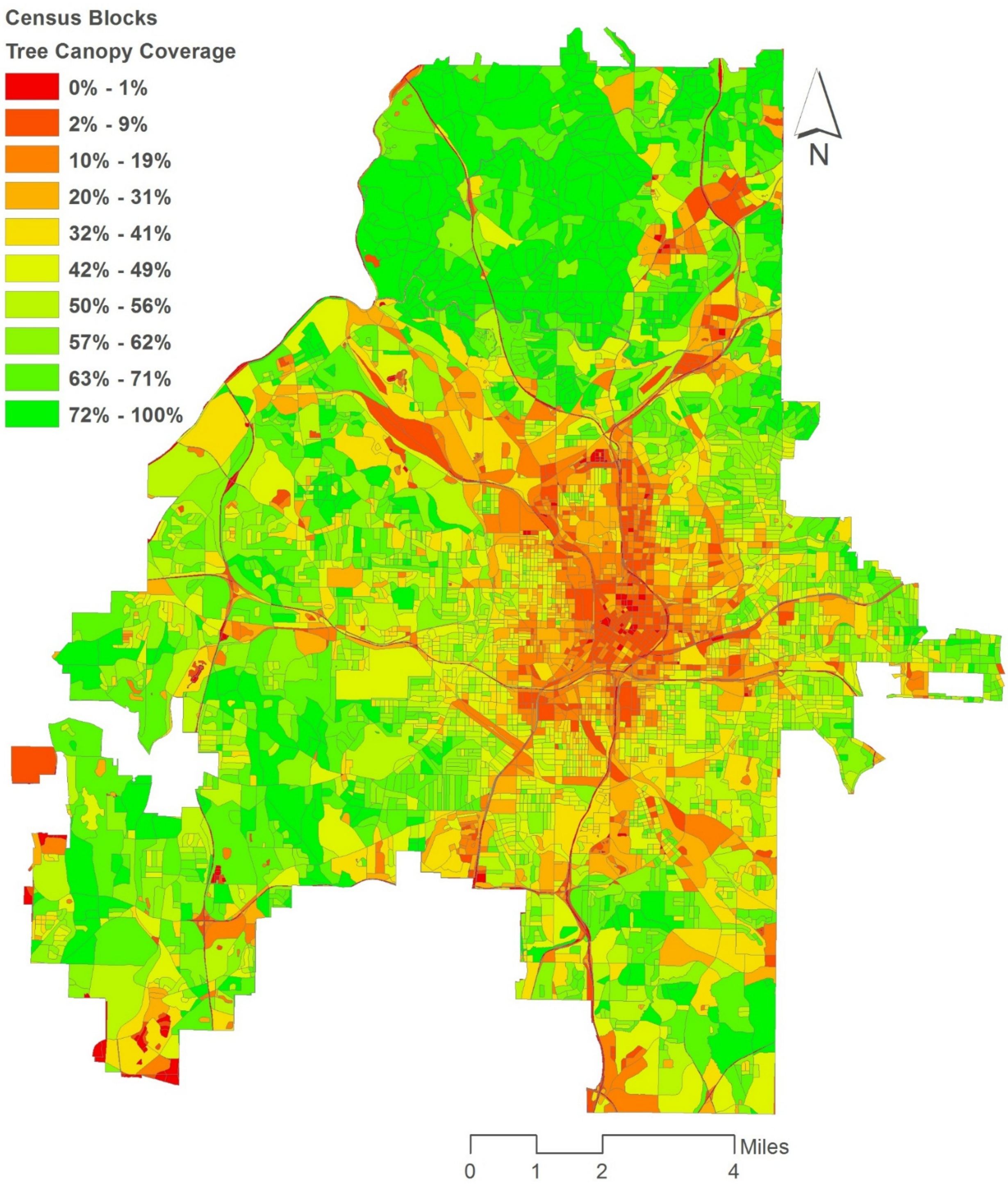
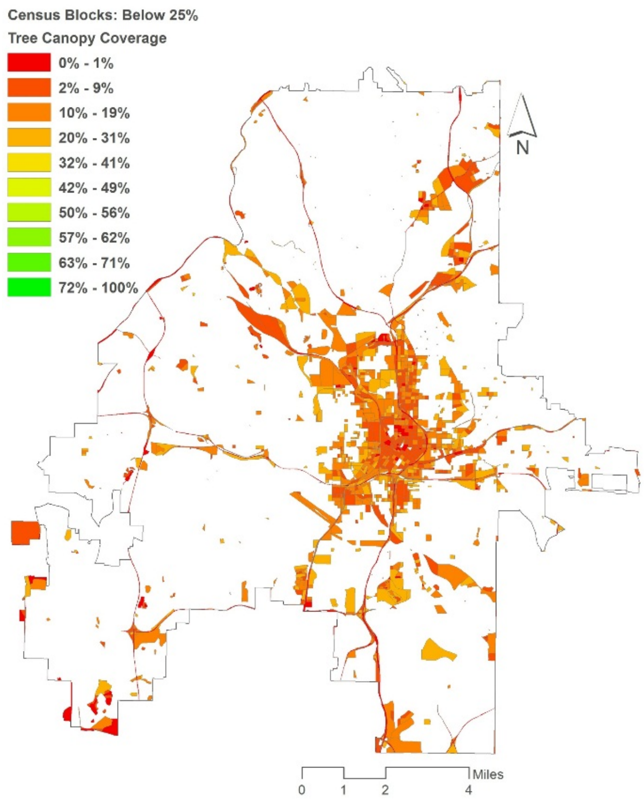


IMAGE 56: URBAN TREE CANOPY COVERAGE PERCENTAGE PER LAND USE TYPE: LOW QUANTILES



IMAGES 57: URBAN TREE CANOPY COVERAGE PERCENTAGE PER LAND USE TYPE: HIGH QUANTILES

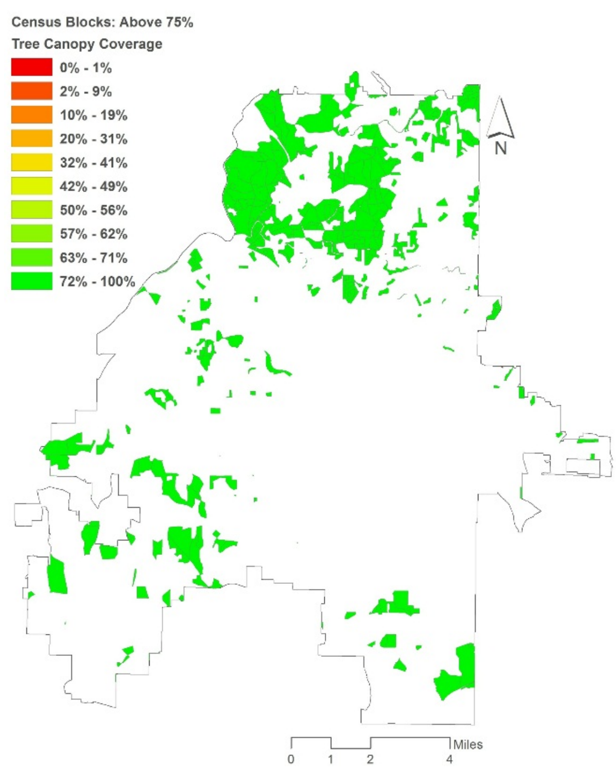


TABLE 11: CENSUS BLOCK STATISTICS RESULTS

	BLOCK CATEGORY	NUMBER OF BLOCKS	TOTAL AREA (acres)	TREE CANOPY AREA (acres)	TREE CANOPY COVERAGE %
CENSUS BLOCKS	TOTAL BELOW 25% CANOPY	2,457	13,779.60	1,667.04	12.10%
	TOTAL ABOVE 75% CANOPY	463	11,593.55	9,381.95	80.92%

Political

The last section, political, is an addition to the four original categories outlined by the initial literature review in chapter two. It is obvious from the previous sections that the City of Atlanta does not possess an ideal urban tree canopy in all areas of the city. Change is needed to ensure equality. An influential route to strengthen or change policy is to help inform local planners, decision-makers, and stakeholders of current conditions. For instance, a planner could approach Kwanza Hall of District 2, Ivory Lee Young of District 3, or Cleta Winslow of District 4 for help in City Council to address the lowest tree canopy coverage in the city (seen in image 58). Table 12 outlines the total area, total canopy coverage area, and canopy coverage percentage for each City Council District.

IMAGE 58: URBAN TREE CANOPY COVERAGE PERCENTAGE PER CITY COUNCIL DISTRICT

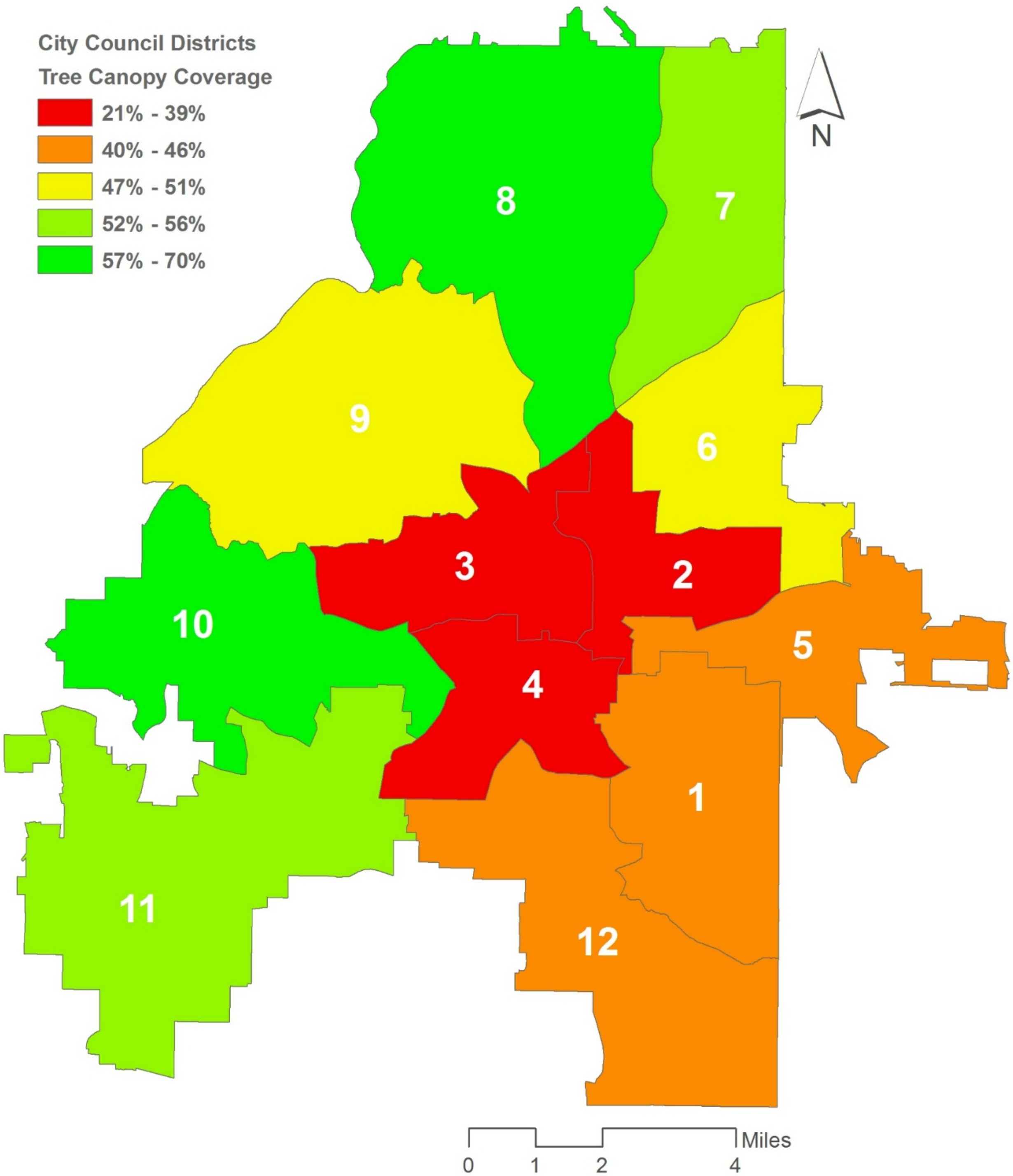


TABLE 12: CITY COUNCIL DISTRICT STATISTICS RESULTS

CITY COUNCIL DISTRICTS	COUNCIL DISTRICT	TOTAL AREA (acres)	TREE CANOPY AREA (acres)	TREE CANOPY COVERAGE %
	1	6,236.51	2,614.20	41.92%
	2	3,682.21	772.24	20.97%
	3	4,703.86	1,783.28	37.91%
	4	4,056.56	1,580.61	38.96%
	5	4,547.31	2,027.17	44.58%
	6	4,942.08	2,521.86	51.03%
	7	5,937.13	3,129.82	52.72%
	8	12,407.26	8,642.82	69.66%
	9	10,621.07	5,152.06	48.51%
	10	7,670.05	4,373.53	57.02%
	11	11,961.44	6,679.10	55.84%
	12	8,930.47	4,093.28	45.83%

Another influential route for changing or aiding policy is through the city's stakeholders. The citizens of the neighborhood planning units (NPUs) are a very organized group of Atlanta stakeholders. Attending a meeting for NPUs L, M, Q, and V could help a planner to inform the citizen stakeholders of the inequitable distribution of the urban tree canopy coverage across the city (seen in image 59). Likewise, approaching a citizen from NPU A, which has the highest density of tree canopy coverage at 74 percent, to act as a tree canopy advocate could prove beneficial in equity measures. Table 13 outlines the total area, the tree canopy coverage area, and canopy coverage percentage for each of the NPUs.

IMAGE 59: URBAN TREE CANOPY COVERAGE PERCENTAGE PER NEIGHBORHOOD PLANNING UNIT

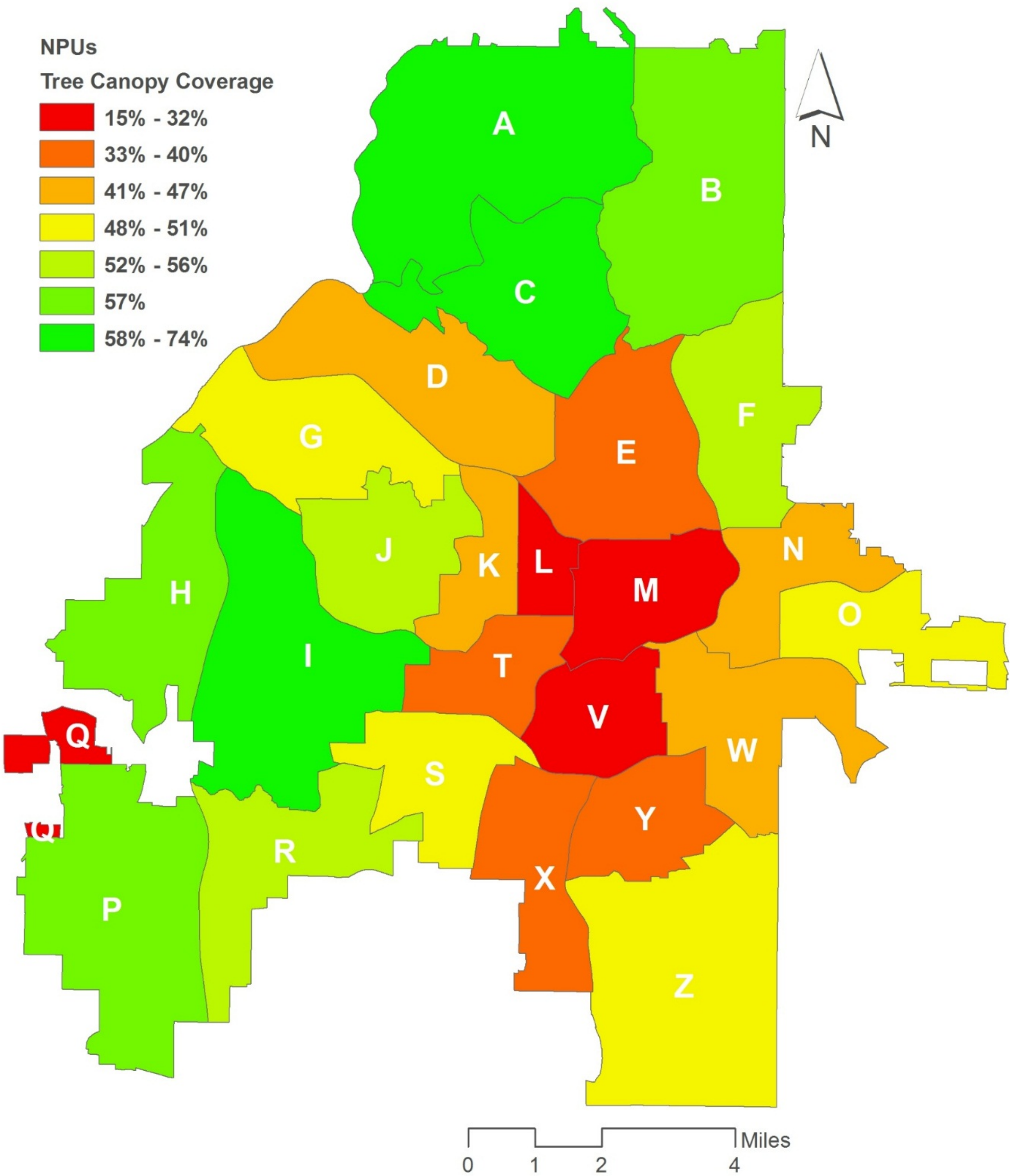


TABLE 13: NEIGHBORHOOD PLANNING UNIT STATISTICS RESULTS

NEIGHBORHOOD PLANNING UNITS

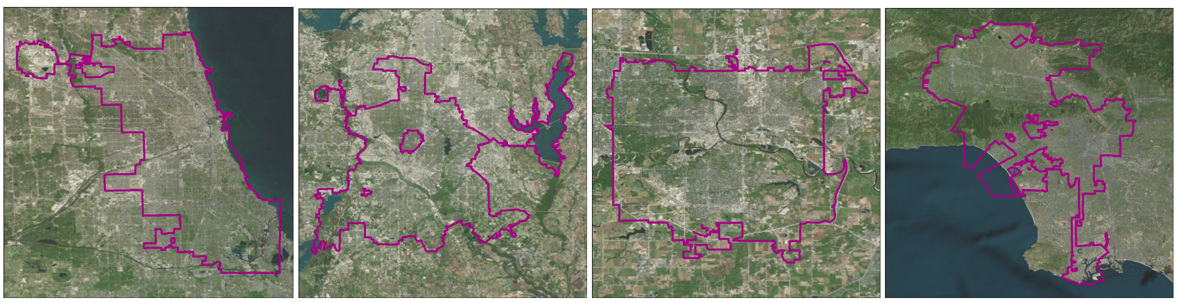
NPU	TOTAL AREA (acres)	TREE CANOPY AREA (acres)	TREE CANOPY COVERAGE %
A	7,316.80	5,413.01	73.98%
B	6,515.61	3,652.26	56.05%
C	3,873.54	2,666.09	68.83%
D	4,150.23	1,659.53	39.99%
E	3,780.16	1,265.81	33.49%
F	3,018.92	1,578.21	52.28%
G	3,597.90	1,769.38	49.18%
H	4,058.23	2,306.90	56.85%
I	6,085.70	3,613.03	59.37%
J	2,840.26	1,496.45	52.69%
K	1,528.32	620.47	40.60%
L	846.20	238.48	28.18%
M	2,421.89	364.73	15.06%
N	2,199.27	975.87	44.37%
O	2,216.46	1,087.91	49.08%
P	5,901.71	3,307.52	56.04%
Q	659.17	208.13	31.58%
R	3,447.94	1,920.58	55.70%
S	2,486.07	1,217.88	48.99%
T	1,750.90	619.73	35.39%
V	2,027.16	546.55	26.96%
W	3,392.32	1,605.43	47.33%
X	2,789.19	1,104.73	39.61%
Y	2,106.45	743.59	35.30%
Z	6,704.12	3,394.03	50.63%

URBAN TREE CANOPY COVER COMPARISON: 15 CITIES

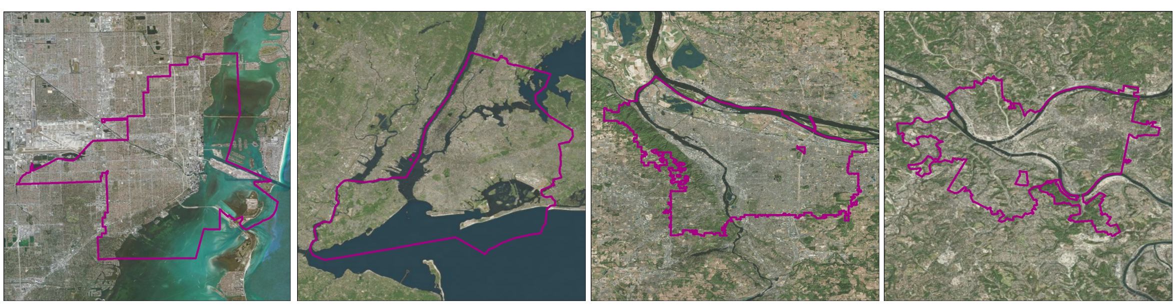
Images 60 through 74 depict an aerial view of the 15 comparison cities, starting with Atlanta and following left to right in alphabetical order.

ATLANTA - ANN ARBOR – AUSTIN - BALTIMORE

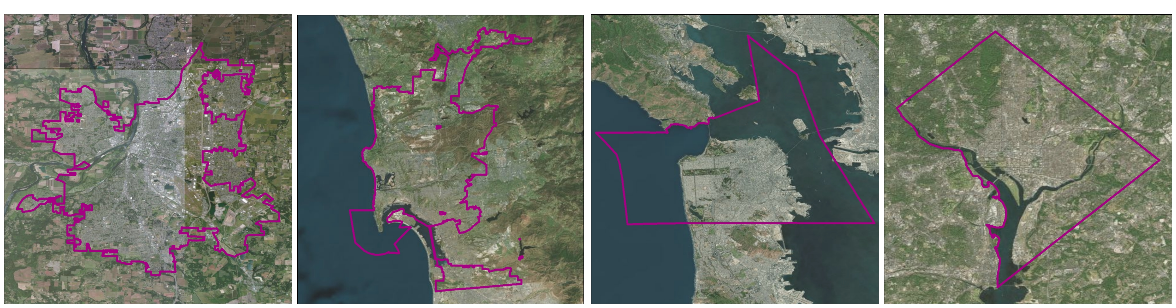
CHICAGO – DALLAS – DES MOINES – LOS ANGELES



DALLAS – NEW YORK CITY - PITTSBURGH – PORTLAND



SALEM - SAN DIEGO – SAN FRANCISCO – WASHINGTON DC



After determining a replicable methodology to catalog the City of Atlanta's urban tree canopy coverage and an internal geography type comparison, an external comparison of tree canopy cover percentage to other cities across the different regions of the U.S. is recommended for ranking purposes. A national ranking allotment has Federal implications, such as possible funding for green projects. Comparable to Atlanta not receiving Federal funding for transportation related development because the city's air quality was so poor, hopefully a high percentage of urban tree canopy coverage can have the opposite effect in potential future Federal funding.

Table 14 below includes: 15 cities' names; populations, population density per acre, and the cities' areas in acres according to the 2010 Census; and the tree canopy area in acres and the percent tree canopy coverage for each city. The final two statistics are derived from individual reports done by numerous sources. Appendix iii includes the same statistics listed in table 14 along with (if applicable) the method for obtaining urban tree canopy data, the study year, the source institution, the source author, and the report title.

TABLE 14: 15 CITY TREE CANOPY COVERAGE COMPARISON

	City	Population (Census 2010)	Population Density (per acre)	City Area (Census 2010, acres)	Tree Canopy Area (acres)	% Tree Canopy
1	Ann Arbor	113,934	6.24	18,264	6,015	32.93%
2	Austin	790,390	4.15	190,656	61,010	32.00%
3	Baltimore	620,961	11.99	51,802	14,130	27.28%
4	Chicago	2,695,598	18.50	145,683	25,058	17.20%
5	Dallas	1,197,816	5.50	217,933	64,280	29.50%
6	Des Moines*	203,433	3.93	51,757	12,466	24.09%
7	Los Angeles^	3,792,625	12.64	299,949	52,493	17.50%
8	Miami	399,457	17.40	22,957	4,821	21.00%
9	New York City	8,244,910	42.57	193,690	44,509	22.98%
10	Pittsburgh	305,704	8.63	35,437	14,883	42.00%
11	Portland^	3,831,073	44.86	85,395	24,118	28.24%
12	Salem, OR^	154,637	5.04	30,656	7,120	23.23%
13	San Diego^	1,307,402	6.28	208,122	27,056	13.00%
14	San Fancisco	805,235	26.84	29,997	8,699	29.00%
15	Washington DC	601,723	15.40	39,072	13,673	34.99%
	Atlanta	**420,005**	**4.91**	**85,494**	**44,841**	**52.45%**

Compared to all of the other cities, Atlanta has the highest percentage of tree canopy coverage by a margin of over 10 percent. This is 52 percent of tree canopy coverage for Atlanta compared to the 42 percent of Pittsburgh, PA. The city with the lowest percentage of tree canopy coverage is San Diego, CA; Atlanta beats San Diego by an almost 40 percent margin. In comparing actual acreage for the cities' tree canopy coverage, Atlanta does not have the highest acreage, rather the city comes in fourth. Dallas, Austin, and Los Angeles all have higher acreages of tree canopy. However, Atlanta is less than half of the size of each of those cities respectively.

FURTHER ACTION

Where can the City of Atlanta further the growth, management, and maintenance of urban vegetation and urban tree canopy coverage?

Land Suitability Analysis

After the initial inventory of urban vegetation and tree canopy coverage was collected and mapped, the images clearly illustrated that there are certain areas of the City of Atlanta that need attention in respect to the percent of land coverage. Even though the areas that do not have as much vegetation and tree canopy coverage are initially apparent, other factors that could hinder growth may not be noticeable. One way to approach the possible future state of urban vegetation and tree canopy coverage is to conduct a land suitability analysis. There are numerous factors to consider in such an endeavor, two are which are existing city parks and pervious versus impervious surfaces. First, extending the existing parks can help increase the green land cover, and connecting parks through expansion can create conservation corridors, which help natural habitats and species to grow and thrive.

The other factor to consider, surface types, takes into account whether or not water and the natural environment is exposed to the ground (pervious) or if the land is covered with development and no outside forces can touch the ground (impervious). In a land suitability analysis, the user can rank the impervious surfaces differently to allocate more and less appropriate areas for regreening and lessening the threat of development on the natural environment. For instance, parking covers an immense amount of the land in the central city with little return to society. In a land suitability analysis, the impervious parking land use and coverage is marked as the most suitable for regreening of the impervious surface class. Conservsely, sidewalks are ranked as the least suitable of the impervious surface class to be regreened because they provide large benefits for pedestrians in a traffic-ridden city.

Overall, a land suitability analysis utilizing existing parks' proximity to one another and regreening the more undesireable imprevious surfaces, along with seemingly numerous other input possibilities, yields areas within the city that are suitable for the addition of urban vegetation and new tree canopy coverage.

Image 75 illustrates the four prominent types of impervious surfaces in the City of Atlanta (parking, driveways, roads, and sidewalks) along with all of the existing parks. Table 15 oulines the the area and the percent of the city's total area that each of the impervious surfaces and parks represent. Existing parks represent less than 5 percent of the city's total land area compared to over 20 percent that is covered by impervious surfaces. Parking lots alone represent almost 8 percent of the city's land cover; that is almost twice as much as our city's existing parks.

IMAGE 75: MAP OF 4 PREVALENT IMPERVIOUS LAND COVERS AND EXISTING CITY PARKS

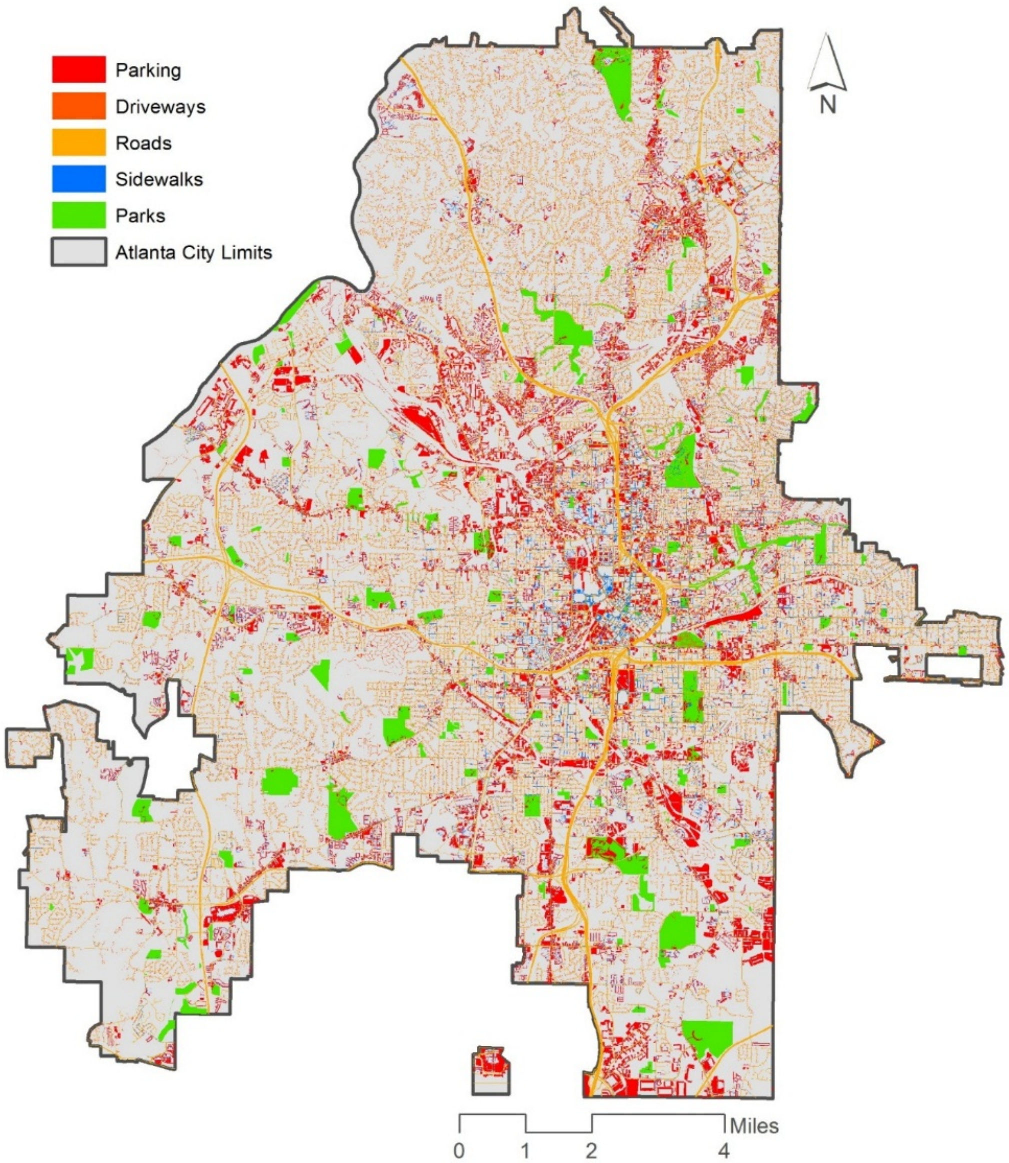


TABLE 15: IMPERVIOUS SURFACES AND PARKS STATISTICS RESULTS

	Land Use Type	Area (acres)	Total % of City
Impervious Surfaces	Parking	6,780.48	7.91%
	Driveways	2,738.71	3.20%
	Roads	6,837.95	7.98%
	Sidewalks	1,457.57	1.70%
	Impervious Total	17,814.71	**20.78%**
	Existing Parks	3,751.64	**4.38%**
	City Total	85,717.42	100.00%

Repeated and Continual Analysis

One of the main purposes of this study is to determine an appropriate and relatively simple methodology for determining the City of Atlanta's urban vegeation land cover classes with specific importance placed on the urban tree canopy coverage. After much time, effort, and experimentation, the human-defined classification process of a supervised approach performed from an NDVI subset of the original raw image has proved not only adequate but more accurate on multiple levels than the computer-defined process of an unsupervised classification. Thus, follow-up analyses on images from different years as well as different months of years are not only suggested but encouraged. Analyzed images from similar months but from different years will yield any change in vegetation and tree canopy coverage. Images from a similar year but a different month (leaf on versus leaf off months, or summer versus winter) yield a differentiation between evergreen and deciduous trees. Using a combination of analyzing images from different months as well as different years will output a very conclusive change detection trend for both evergreen and deciduous trees.

In Depth Demographic Survey

An importance next step is to determine where the socially vulnerable populations live compared to urban vegetation and tree canopy coverage. It is important to plan for these socioeconomically disadvantaged residents. If there is a disconnect between these populations' locations and the areas of the densely located vegetation and tree canopy coverage. As outlined above in great detail, along with socioeconomical, urban vegetation and tree canopy coverage has many positive externalities, environmentally, hydrologically, and via urban design. Policy efforts and planning practices to help align these two populations, the less socially and economically capable residents and the urban vegetation, will certainly have both long term and immediate positive outcomes.

Regional Comparison

Finally, after in depth further actions of a land suitability analysis with multiple guiding inputs, repeat and continual analysis, and an in depth demographic survey, the last action to take to encourage the growth, maintenance, and management of Atlanta's urban vegetation and tree canopy coverage is for on-going comparison of the city's statistics to other cities, to the state of Georgia, and to its region. Continual internal analysis of Atlanta over time is very important, but so is the external comparison with other demographics that vary in size and location. We want municipalities, counties, states, regions, and more to learn with each other and grow from one another's example.

REFERENCES

AMEC Environment & Infrastructure Denver, Colorado (2011, August). GIS Analysis of Salem's Potential Urban Tree Canopy. Retrieved from http://www.cityofsalem.net/Residents/Parks/UrbanForestry/Documents/Salem%20Phase-2%20UTC%20Technical%20Report%2009012011.pdf.

Atlanta Regional Commission. (2013). ARIS GIS Files (ZIP) [Shapefiles]. Retrieved from http://www.atlantaregional.com/info-center/gis-data-maps/gis-data.

Avril, T. (2011). University of Pennsylvania study links vacant-lot cleanups, reduced gun crime. *Philly.com.* Retrieved from http://articles.philly.com/2011-11-25/news/30441289_1_gun-assaults-crime-rates-gun-crime.

Barnoaiea, I. (2010). Forest structure analysis on very high resolution images. *AES Bioflux: Advances in Environmental Sciences- International Journal of the Bioflux Society, 2* (2), 239-251. Retrieved from ehis.ebscohost.com.

Cadenasso, M. L., Pickett, S. T. A., & Schwarz, K. (2007). Spatial heterogeneity in urban ecosystems: reconceptualizing land cover and a framework for classification. *Frontiers in Ecology and the Environment, 5* (2), 80-88. Retrieved from www.esajournals.org.

Center for Biodiversity and Conservation (n.d.). Biodiversity Informatics Facility: Remote Sensing Resources. Retrieved from http://biodiversityinformatics.amnh.org/index.php?section_id=34&content_id=131.

Georgia Institute of Technology. (2012). *Tree Canopy Baseline Study for the City of Atlanta.* Atlanta, Georgia: Center for Geographic Information Systems (CGIS), & Center for Quality Growth & Regional Development (CQGRD).

Chanussot, J., Benediktsson, J. A., & Fauvel, M. (2006). Classification of Remote Sensing Images From Urban Areas Using a Fuzzy Possibilistic Model. *IEEE Transactions on Geoscience and Remote Sensing, 3* (1), 2828-2838. Retrieved from ieeexplore.ieee.org.

City Policy Associates, Washington, D.C. Protecting and Developing the Urban Tree Canopy: a 135-City Survey. Retrieved from http://www.usmayors.org/trees/treefinalreport2008.pdf.

Congalton, R. G. (1991). A Review of Assessing the Accuracy of Classifications of Remotely Sensed Data. *Remote Sens. Environ., 37* (1991), 35-46. Retrieved from http://www.srnr.arizona.edu/rnr/rnr419/publications/Congalton1991.pdf.

Dwyer, M. C., & Miller, R. W. (1999). Using GIS to Assess Urban Tree Canopy Benefits and Surrounding Greenspace Distributions. *Journal of Arboriculture*, *25* (2), 102-107. Retrieved from cambria.cgu.edu.

Fauvel, M., Chanussot, J., & Benediktsson, J. A. (2006). Decision Fusion for the Classification of Urban Remote Sensing Images. *IEEE Transactions on Geoscience and Remote Sensing, 44* (10), 2828-2838. Retrieved from ieeexplore.ieee.org.

Grove, M. J., O'Neil-Dunne, J., Pelletier, K., Nowak, D., & Walton, J. (2006, 12 July). A Report on New York City's Present and Possible Urban Tree Canopy. Retrieved from http://www.nrs.fs.fed.us/nyc/local-resources/downloads/Grove_UTC_NYC_FINAL.pdf.

Hanou, I. (2010, April). Ann Arbor, Michigan: Urban Tree Canopy (UTC) Assessment. Retrieved from http://www.a2gov.org/government/publicservices/fieldoperations/forestry/Documents/Ann%20Arbor%20UTC%20Report%20-%20AMEC%20-%20April-10.pdf.

Hanou, I. (2010, January). The Roadmap to Tree Planning & Planting Success: the Potential Urban Forest of Dallas, Texas. Retrieved from http://www.urbanforestrysouth.org/resources/library/ttresources/201croadmap-to-tree-planning-and-2.

Heynen, N., & Lindsey, G. (2003). Correlate of Urban Forest Canopy Cover: Implications for Local Public Works. *Public Works Management & Policy, 8* (33), 33-47. DOI: 10.1177/1087724X03008001004.

Heynen, N., Perkins, H. A., & Roy, P. (2006). The Political Ecology of Uneven Urban Green Space: The Impact of Political Economy on Race and Ethnicity in Producing Environmental Inequality in Milwaukee. *Urban Affairs Review*, *42* (3), 3-25. DOI: 10.1177/1078087406290729.

Kilberg, D., Martin, M., & Bauer, M. (2012, January 5). Mapping Urban Tree Cover: Object Oriented Image Analysis of QuickBird and LiDAR Data. Retrieved from www.ramseygis.org.

Kinzig, A. P., Warren, P., Martin, C., Hope, D., & Katti, M. (2005). The Effects of Human Socioeconomic Status and Cultural Characteristics on Urban Patterns of Biodiversity. *Ecology and Society 10* (1): 23. Retrieved from http://www.ecologyandsociety.org/vol10/iss1/art23/.

McPherson, E. G., & Rowntree, R. (1993). Energy Conservation Potential of Urban Tree Planting. *Journal of Arboriculture, 19* (6). Retrieved from www.lewistonpublicschools.org.

McPherson, G., & Simpson, J. (2007, 31 March). Los Angeles One Million Tree Canopy Cover Assessment Final Report. Retrieved from http://www.fs.fed.us/psw/programs/uesd/uep/products/psw_cufr689a_MillionTreesLA_final_web.pdf

Monear, J., & Grubisich, M. (2009). "Roadmap to Tree Planning and Planting" Dallas, TX: a New Innovative Approach to an Old Problem. *Texas Trees Foundation*. Retrieved from http://www.dallascityhall.com/council_briefings/briefings0309/RoadmapTreePlanting_03042009.pdf.

Moran, E. F. (2010). Land Cover Classficiation in a Complex Urban-Rural Landscape with Quickbird Imagery. *National Institute of Public Health: Photogramm Eng Remote Sensing, 76* (10), 1159-1168. Retrieved from http://www.ncbi.nlm.nih.gov/pmc/articles/pmc3105321/.

Nowak, D. J. (2006). Institutionalizing urban forestry as a "biotechnology" to improve environmental quality. *Urban Forestry & Urban Greening, 5* (2006), 93-100. Retrieved from www.sciencedirest.com.

Nowak, D. J., Hoehn III, R. E., Crane, D. E., & Stevens, J. C. (2010, February). Chicago's Urban Forest. Retrieved from http://www.itreetools.org/resources/reports/Chicago's%20Urban%20Forest.pdf.

Nowak, D. J., Noble, M. H., Sisinni, S. M., & Dwyer, J. F. (2001). People & Trees: Assessing the US Urban Forest Resource. *Journal of Forestry, 99* (3), 37-42. Retrieved from www.ingentaconnect.com.

Nowak, D. J., Rowntree, R. A., McPherson, E. G., Sisinni, S. M., Kerkmann, E. R., & Stevens, J. C. (1996). Measuring and analyzing urban tree cover. *Landscape and Urban Planning, 36* (1996), 49-57. Retrieved from www.sciencedirect.com.

O'Neil-Dunne, J. (2009, 17 April). A Report on Washington, D.C.'s Existing and Possible Urban Tree Canopy. Retrieved from http://www.fs.fed.us/nrs/utc/reports/UTC_Report_DC.pdf.

O'Neil-Dunne, J. (2009, 13 May). A Report on the City of Des Moines Existing and Possible Urban Tree Canopy. Retrieved from http://www.fs.fed.us/nrs/utc/reports/UTC_Report_DesMoines.pdf

O'Neil-Dunne, J. (2009, 16 September). A Report on the City of Baltimore's Existing and Possible urban Tree Canopy. Retrieved from http://nrs.fs.fed.us/urban/utc/reports/UTC_Report_BACI_2007.pdf

Portland Parks & Recreation, City Nature Urban Forestry (2007, October). Portland's Urban Forest Canopy: Assessment and Public Tree Evaluation. Retrieved from http://www.portlandoregon.gov/parks/article/171829.

Ruckman, R. M. The Urban Ecosystem's Effect on Energy Use in Austin. Retrieved from http://soa.utexas.edu/portfolio/rmr597/files/uhie-mitigation.pdf.

Sanders, R. A. (1986). Urban Vegetation Impact on the Hydrology of Dayton, Ohio. *Urban Ecology, 9* (1986), 361-376. Retrieved from www.sciencedirect.com.

Simpson, J. R., & McPherson, E. G. (2007, December). San Francisco Bay Area State o the Urban Forest Final Report. Retrieved from http://www.fs.fed.us/psw/programs/uesd/uep/ Zproducts/2/psw_cufr719_SFBay.pdf.

Tree Pittsburgh (2011). State of the PGH Urban Forest. Retrieved from http://treepittsburgh.org/sites/default/files/PDFs/ufmp_davey_stateofthepghurbanforest.pdf.

US Census Bureau. (2013). 2012 TIGER/Line Shapfiles [Shapefiles]. Retrieved from http://www.census.gov/cgi-bin/geo/shapefiles2012/main

US Census Bureau. (2013). State & County QuickFacts: Atlanta (city), Georgia [Demographic Data]. Retrieved from http://quickfacts.census.gov/qfd/states/13/1304000.html.

US Department of Agriculture Forest Service (2003, July). Urban Ecosystem Analysis San Diego, California. Retrieved from http://www.ufei.org/files/pubs/sandiegouea.pdf

USGS: Science for a Changing World. (2010, January). Greenness of the Conterminous U.S. Retrieved from http://ivm.cr.usgs.gov/whatndvi.php.

Veldkamp, A., & Verburg, P. H. (2004). Modelling land use change and environmental impact. *Journal of Environmental Management 72* (1-2), 1-3. DOI: 10.1016/j.jevnman.2004.04.004.

APPENDIX

i. Supervised Classification Accuracy Assessment Report and Error Matrix

CLASSIFICATION ACCURACY ASSESSMENT REPORT

Image File : c:/documents and settings/gcampbell31/desktop/results/atlsupclassn7.img
User Name : gcampbell31
Date : Thu Apr 18 13:32:58 2013

ERROR MATRIX

Reference Data

Classified Data	Background	Class 1	Class 2	Class 3
Background	0	0	0	0
Class 1	1	33	25	4
Class 2	0	15	188	3
Class 3	0	6	3	11
Class 4	0	1	0	0
Column Total	1	55	216	18

Reference Data

Classified Data	Class 4	Row Total
Background	0	0
Class 1	1	64
Class 2	0	206
Class 3	5	25
Class 4	4	5
Column Total	10	300

----- End of Error Matrix ----- ACCURACY TOTALS

Class Name	Reference Totals	Classified Totals	Number Correct	Producers Accuracy	Users Accuracy

Class	0	1	0	0	---	---
Class	1	55	64	33	60.00%	51.56%
Class	2	216	206	188	87.04%	91.26%
Class	3	18	25	11	61.11%	44.00%
Class	4	10	5	4	40.00%	80.00%
Totals	300	300	236			

Overall Classification Accuracy = 78.67%

----- End of Accuracy Totals ----- Page 1

KAPPA (K^) STATISTICS

Overall Kappa Statistics = 0.5372

Conditional Kappa for each Category.

Class Name Kappa

---------- ----- Class 0 0.0000

Class 1 0.4069

Class 2 0.6879

Class 3 0.4043

Class 4 0.7931

----- End of Kappa Statistics -----

ii. Unsupervised Classification Accuracy Assessment Report and Error Matrix

CLASSIFICATION ACCURACY ASSESSMENT REPORT
--- Image File : d:/spring 13/results/atlucn3.img
User Name : gcampbell31
Date : Wed Apr 24 00:56:46 2013

ERROR MATRIX

Reference Data

Classified Data	Background	Class 1	Class 2	Class 3
Background	0	0	0	0
Class 1	0	34	4	24
Class 2	0	3	11	17
Class 3	0	9	10	101
Class 4	0	0	1	0
Class 5	0	3	0	1
Column Total	0	49	26	143

Reference Data

Classified Data	Class 4	Class 5	Row Total
Background	0	0	0
Class 1	3	1	66
Class 2	6	3	40
Class 3	3	5	128
Class 4	38	8	47
Class 5	1	14	19
Column Total	51	31	300

----- End of Error Matrix ----- ACCURACY TOTALS

Class Name | Reference Totals | Classified Totals | Number Correct | Producers Accuracy | Users Accuracy
---------- ---------- ---------- ------- --------- -----

Class	0	0	0	0	---	---
Class	1	49	66	34	69.39%	51.52%
Class	2	26	40	11	42.31%	27.50%
Class	3	143	128	101	70.63%	78.91%
Class	4	51	47	38	74.51%	80.85%
Class	5	31	19	14	45.16%	73.68%

Totals	300	300	198

Overall Classification Accuracy = 66.00%

----- End of Accuracy Totals -----

KAPPA (K^) STATISTICS

Overall Kappa Statistics = 0.5251

Conditional Kappa for each Category.

Class Name		Kappa
Class	0	0.0000
Class	1	0.4205
Class	2	0.2062
Class	3	0.5969
Class	4	0.7693
Class	5	0.7065

----- End of Kappa Statistics -----

iii. 15 City Urban Tree Canopy Cover Comparison with Method, Year, Source Institution, Source Author, and Report Web Link (if applicable)

City	Population (Census 2010)	Population Density (per acre)	City Area (Census 2010, acres)	UTC Area (acres)	UTC%	Method	Year	Source Institution	Source Author	Report
nn Arbor	113,934	6.24	18,264	6,015	32.9	Multispectral Remote Sensing	2010	AMEC Earth & Environmental	Hanou, I.	Ann Arbor, Michigan Urban Tr Canopy (UTC) Assessment
ustin	790,390	4.15	190,656	61,010	32.0	Aerial Photography Pixel Analysis		Austin Parks and Recreation Department	Ruckman, R. M.	The Urban Ecosystem's Effect Energy Use in Austin
altimore	620,961	11.99	51,802	14,130	27.3	Aerial Imagery	2009	Rubenstein School of the Environmental & Natural Resources, University of Vermont	O'Neil-Dunne, J.	A Report on the City of Baltim Existing and Possible Urban Tr Canopy
hicago	2,695,598	18.50	145,683	25,058	17.2			USDA Forest Service, Northeastern Research Station	Nowak, D. J., Hoehn III, R. E., Stevens, J. C., & Fisher, C. L.	Assessing Urban Forest Effect Values: Chicago's Urban Fores
allas	1,197,816	5.50	217,933	64,280	29.5	Multispectral Remote Sensing	2010	AMEC Texas Trees Foundation	Hanou, I.	The Roadmap to Tree Plannin Planting Success: The Potentia Forest of Dallas, Texas
es Moines*	203,433	3.93	51,757	12,466	26.8	Satellite Imagery and LiDAR	2009	Rubenstein School of the Environmental & Natural Resources, University of Vermont	O'Neil-Dunne, J.	A Report on the City of Des M Existing and Possible Urban Tr Canopy
os Angeles^	3,792,625	12.64	299,949	52,493	17.5	QuickBird Remote Sensing	2007	Center for Urban Forest Research, Pacific Southwest Research Station, USDA Forest Service; & Department of Land, Air, and Water Resources, University of California Davis	McPherson, G. & Simpson, J.; Xiao, Q., & Wu, C.	Los Angeles One Million Tree Cover Assessment Final Repor
liami	399,457	17.40	22,957	4,821	21.0		2008	The United States Conference of Mayors	City Policy Associates, Washington, D.C.	Protecting and Developing the Tree Canopy: A 135-City Surve
ew York City	8,244,910	42.57	193,690	44,509	23.0	Satellite Imagery and LiDAR	2006	USDA Forest Service, Northeastern Research Station	Grove, M. G., O'Neil-Dunne, J., Pelletier, K., Nowak, D., & Walton, J.	A Report on New York City's P and Possible Urban Tree Canc
ittsburgh	305,704	8.63	35,437	14,883	42.0	Satellite Imagery and LiDAR	2011	USDA Forest Service: Tree Canopy Assessment Protocols		State of the PGH Urban Forest
ortland^	3,831,073	44.86	85,395	24,118	28.2		2007	Portland Parks & Recreation, City Nature Urban Forestry	Karps, J., Darling, J., Allen, M., Hill, N., Montegna, A., & Seyb, C.	Portland's Urban Forest Cano Assessment and Public Tree Evaluation
alem, OR^	154,637	5.04	30,656	7,120	23.2	Satellite Imagery	2011	AMEC Environment & Infrastructure		GIS Analysis of Salem's Potent Urban Tree Canopy
an Diego^	1,307,402	6.28	208,122	27,056	13.0	Landsat Satellite 30 m	2003	USDA Forest Service		Urban Ecosystem San Diego, California: Calculating the Val Nature
an Fancisco	805,235	26.84	29,997	8,699	29.0	Satellite Imagery	2007	USDA Forest Service, Pacific Southwest Research Station	Simpson, J. R. & McPherson, E. G.	San Francisco Bay Area State Urban Forest Final Report
								Rubenstein School of the Environmental		A Report on Washington, D.C